Testing and Validating a Coherence-Based Model for Decision-Making and Search

Sophie E. Scharf

Inaugural Dissertation

Submitted in partial fulfillment of the requirements for the degree Doctor of Social Sciences in the Graduate School of Economic and Social Sciences at the University of Mannheim

Thesis Defense:
March 29, 2021

Supervisors:
Prof. Dr. Arndt Bröder
Prof. Dr. Andreas Glöckner

Dean of the School of Social Sciences:
Prof. Dr. Michael Diehl

Thesis Reviewers:
Prof. Dr. Edgar Erdfelder
Prof. Dr. Daniel Heck

Defense Committee:
Prof. Dr. Arndt Bröder
Prof. Dr. Edgar Erdfelder
Prof. Dr. Daniel Heck

For my family

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Summary

Recently, Jekel et al. (2018) proposed the *integrated coherence-based decision and search* model (iCodes), which predicts decision-making and information search in multi-cue decision tasks. This model assumes that decision-makers strive for coherence-maximization and that this pursuit is represented by an iterative spread of activation through a network that represents all relevant information of the current decision. The goal of my thesis is to evaluate iCodes as a general theory of decision-making and information search, to test its predictions by employing experimental methods, computational modeling and process tracing, and finally to critically discuss its merits in the field of judgment and decision-making research (JDM) as a whole.

A unique contribution of iCodes compared to other theories in JDM is its prediction that people show a tendency to search for information on the option that is currently supported by the available evidence, also referred to as the *attraction search effect*. In the first manuscript, we could show that the attraction search effect is a robust finding and generalizes to a variety of different tasks. This finding supported a broad range of applicability for iCodes' predictions for information search. In the second manuscript, we could show that iCodes can account for the effect of a theoretically motivated moderator of the attraction search effect, namely that rating the attractiveness of options before search increases the tendency to search for information on the attractive option. We further validated the assumed, underlying information-search process by showing that a model-inherent parameter can account for the effect of attractiveness ratings. The third manuscript showed that iCodes is not only able to predict behavioral information search but is also able to predict gaze behavior in decision-making. It further highlighted the role of coherence for attention allocation in decision tasks. In sum, my thesis contributes to the theoretical advancement of research in JDM and emphasizes the importance of formalized theories.

Manuscripts

The research for this dissertation was conducted in the *Center for Doctoral Studies in Social Sciences* (CDSS) of the *Graduate School of Economic and Social Sciences* (GESS) at the University of Mannheim. In three manuscripts, I test iCodes' predictions for information search to assess its empirical content and to contribute to theory development in research on Judgment and Decision Making. Of these three manuscripts, one is published and two are submitted for publication.

I evaluate iCodes' theoretical properties by testing its generalizability (Manuscript I), validating its process assumptions (Manuscript II) and testing its predictions for attention allocation (Manuscript III). The main text of this thesis provides an overview of the three manuscripts, details on the experimental implementations and statistical analyses can be found in the original manuscripts appended to this thesis.

Manuscript I

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488-512.

Manuscript II

Scharf, S. E., Jekel, M., & Glöckner, A. (2021). *Testing an extension of the iCodes model to account for situation, person, and task specific variation in the attraction search effect.* Manuscript submitted for publication.

Manuscript III

Scharf, S. E., Bröder, A., Jekel, M., & Glöckner, A. (2021). *Coherence influences on attention allocation and visual information search in decisions with open information displays.* Manuscript submitted for publication.

1 Introduction

In psychological research on Judgment and Decision Making (JDM), the main focus lies on how people integrate information in order to choose a course of action (Hastie, 2001). As this research question is rather broad, it generated a wealth of different research streams, ranging from normative theories that investigate the rationality of human decision-making to more descriptive theories that aim to describing the cognitive processes behind human decision-making (Hastie & Dawes, 2010). Further, the field has been historically divided into research on judgments (i.e., how information is integrated to form beliefs) and research on decisions (i.e., how to choose between options; cf. Goldstein & Hogarth, 1997; Hastie, 2001). Additionally, due to the ubiquity of situations that necessitate judgements or decisions, a variety of other sub-disciplines of psychology have investigated these two processes in connection to their foci of research (see Goldstein & Hogarth, 1997, for a review). This variety of JDM research lead to different research traditions that employ different paradigms and methods but at the same time often overlap to some extent (Goldstein & Hogarth, 1997).

One consequence of the wide spectrum of JDM research is that "the number of theories that peacefully coexist in the literature is constantly growing" (Glöckner & Betsch, 2011, p. 711). In their article, Glöckner and Betsch (2011) identified the lack of well-specified theories as one underlying cause for the accumulation of weak theories in JDM. Without proper specification, these theories make only weak predictions about decision behavior and are, therefore, difficult to falsify. Such theories can often be adjusted to explain anything and, thus, ultimately explain nothing (Glöckner & Betsch, 2011). The lack of well-specified theories that make precise statements about their antecedents, predicted consequences, and boundary conditions impedes the scientific progress in JDM and psychology in general (C. J. Ferguson & Heene, 2012; Glöckner & Betsch, 2011; Glöckner et al., 2018; Smaldino, 2019). One potential solution suggested by Glöckner and Betsch (2011; and also Glöckner et al., 2018; Smaldino, 2019) was to propose more formalized theories that make precise predictions and are, therefore, easily testable.

With the introduction of the *integrated coherence-based decision and search model* (iCodes), Jekel et al. (2018) proposed such a formalized, computational model that makes precise predictions about information search and decision-making in multiple-cue judgment tasks. iCodes is an extension of the *parallel constraint satisfaction model for decision making* (PCS-DM, Glöckner et al., 2014) that applies its assumed decision-making process to information search and attention allocation. The underlying assumption of iCodes is that information search and decision-making can be understood as outcomes of a coherence-maximization process.

In my thesis, I contribute to the theory development in JDM by evaluating iCodes' properties as a theory and critically testing its predictions. By specifying iCodes' predictions and its scope of application, I provide the foundation for critically assessing its merit as a general theory of decision-making and search. Yet, only if iCodes' predictions are corroborated by empirical evidence, the field of JDM makes scientific and theoretical progress. The empirical tests of iCodes' predictions in my manuscripts enable a critical review of iCodes' corroboration as a theory. In its entirety, my thesis aims to evaluate iCodes' contribution to JDM research and thereby identifying areas of future theoretical developments for iCodes specifically and JDM in general.

In the introduction, I present the background on theories in JDM and introduce iCodes as a new theory of coherence-based decision-making and search. I conclude this introduction by assessing iCodes' theoretical properties and its empirical content, that is, its level of universality as well as the degree of precision of its predictions (cf. Popper, 1935; see also Glöckner & Betsch, 2011). In three manuscripts, I review the degree to which iCodes' predictions were supported by experimental evidence. In Manuscript I, I examined the level of universality by testing one of iCodes' core predictions in different decision contexts (Scharf et al., 2019). In Manuscript II, I assessed the degree of specificity of iCodes by testing a theoretically motivated moderator of its information-search predictions and validating the associated, model-inherent parameter. Lastly, I examined iCodes' scope of application in Manuscript III by testing its predictions for attention allocation. In the discussion, I evaluate the evidence presented in the three manuscripts with regard to iCodes' performance as theory of coherence-based decision-making and information search and compare its properties to other current theoretical accounts in JDM.

Finally, I discuss implications for the future development of iCodes specifically and research on information search in general.

With this thesis, I not only advance the current state of the literature on coherence-based models of decision-making and information search, but also contribute to critically testing, evaluating, and distinguishing theories in JDM. Further, my thesis contributes to establishing and testing more precise theories in the field of JDM and identifying the merits of formalized modeling in psychology in general.

1.1 Theories of Judgment and Decision Making

The origin of modern psychological theories in the field of Judgment and Decision Making (JDM) can be traced back to the 1950s (see Goldstein & Hogarth, 1997). While older theories were mainly concerned with describing decisions from a normative perspective (for a review, see Edwards, 1954), the theoretical focus shifted with the introduction of the concept of bounded rationality (H. Simon, 1955, 1957). With the growing evidence that human decision-making deviates from normative models claiming to represent rationality, more theories were proposed that describe *how* people integrate information in order to decide on a course of action (Goldstein & Hogarth, 1997). These theories investigate a number of different decision problems, often using specialized experimental tasks to tackle their specific research question. The subset of proposed decision-making theories, that are introduced hereafter, are all applicable to multiple-cue decision tasks, in which the information of multiple cues has to be integrated with regard to a subjective or objective decision criterion in order to decide between two or more options. In the following, I review three theoretical approaches that differ in their underlying assumptions for decisions in these tasks. First, I introduce the multi-strategy approach to human decision-making that is often subsumed in the metaphor of the adaptive toolbox (Gigerenzer & Gaissmaier, 2011; Gigerenzer & Todd, 1999; see also Payne et al., 1993; H. Simon, 1957). I, then, expand on theoretical approaches that assume a single, underlying decision-making process that is either based on a process of evidence accumulation (Busemeyer & Johnson, 2004; Krajbich et al., 2010; Lee & Cummins, 2004) or a process of coherence maximization (Glöckner & Betsch, 2008a; Holyoak & Simon, 1999; Rumelhart & McClelland, 1986).

Multi-Strategy Accounts

One of the most influential conceptualizations of human decision-making was the idea that people cope with high computational demands during decision-making by utilizing simplifying decision strategies (Gigerenzer & Gaissmaier, 2011; Payne et al., 1993; H. Simon, 1957). This idea culminated in the proposition that the human mind can be compared to an *adaptive toolbox* from which decision-makers choose different strategies or heuristics to adjust to changing demands of the decision context (Gigerenzer, 2001; Gigerenzer & Gaissmaier, 2011; Gigerenzer & Todd, 1999). These strategies or heuristics often structure the decision processes into sub-processes of information search, information integration, and the decision itself (Gigerenzer, 2001; Gigerenzer & Todd, 1999; Payne et al., 1993). A prominent example of such a strategy is the lexicographic heuristic (Payne et al., 1988, 1993), also known as the take-the-best heuristic (Gigerenzer & Goldstein, 1996). This decision strategy assumes that information on the options under consideration is inspected in order of importance. If the most important cue favors one of the options, information search is stopped and the respective option is chosen. If the information of the cue does not discriminate between options, additional information is searched for, again in order of importance until a decision can be reached. While such single heuristics can describe decisions well in specific situations, several studies have shown that decision-makers may adapt to decision contexts by using different strategies (Bröder & Schiffer, 2006; Dieckmann & Rieskamp, 2007; Payne et al., 1988; Rieskamp & Hoffrage, 2008). Therefore, to adequately describe human decision-making, theories that assume the adaptive use of different decision strategies must specify a mechanism by which decision-makers choose between those strategies and under which circumstances which strategy is applied (Glöckner & Betsch, 2011). To solve this issue, different models have been proposed that trace adaptive strategy selection back to learning processes (Erev & Barron, 2005; Lieder & Griffiths, 2017; Rieskamp & Otto, 2006).

While research supported the adaptive change in decision processes, the multi-strategy approach to decision-making has not been without criticism. In their review, Bröder and Newell (2008) concluded that one of the core assumptions, namely that integrating all relevant decision information is a cognitively costly and time-consuming process and, thus, simplifying strategies are needed, was not unanimously supported by research. Moreover, without a fixed set of specified heuristics with clear criteria for their adaptive selection, such multi-strategy accounts are effectively unfalsifiable as each critical result could be resolved by adding new heuristics or selection criteria (Glöckner & Betsch, 2011; Glöckner et al., 2010; but see also Marewski, 2010, and Scheibehenne et al., 2013, for a response to this criticism). Hence, multi-strategy accounts of decision-making have not only been criticized for their assumptions about cognitive processes but also for their properties as a theory on the meta-level. Thus, Newell (2005) proposed that a single-mechanism account would be an alternative and more parsimonious explanation of the adaptivity in decision behavior (see also Bröder & Newell, 2008).

Evidence-Accumulation Models

One example for such a single-mechanism account is the class of evidence-accumulation models (EAM, Hausmann & Läge, 2008; Lee & Cummins, 2004; see also Decision Field Theory, Busemeyer & Johnson, 2004; or Drift Diffusion Models, Krajbich et al., 2010). These types of models typically assume that evidence for the options is sampled via a stochastic process (Ratcliff et al., 2016). This process stops once enough evidence is accumulated, so that a subjective threshold of evidence is surpassed for one of the options that is subsequently chosen. Such models can adapt their predicted decision behavior to different contexts by adapting their parameters (such as the individual evidence thresholds, Lee & Cummins, 2004; Newell, 2005). EAMs have soon become popular in JDM research as they are more parsimonious than theories that assume multiple decision strategies (Glöckner & Betsch, 2011; Newell, 2005). For instance, Newell and Lee (2011) showed that EAMs described participants' decision behavior best compared to single heuristics and a basic implementation of a multi-strategy model. In addition, EAMs allow for making precise and well-corroborated predictions about process measures, such as response times (Lee & Cummins, 2004; Trueblood et al., 2014) and attention allocation (Fisher, 2017; Krajbich et al., 2012).

The prediction of additional dependent variables increases the overall empirical content of EAMs. Yet, these models include free parameters to account for the adaptability of decision-making behavior, which potentially decreases the precision of their prediction due to an increases of model flexibility (Glöckner & Betsch, 2011).[1] Besides its flexibility, a more substantial concern regarding EAMs is their

[1]As already stated by Glöckner and Betsch (2011) this criticism is not unique to EAMs but

prediction of the information-search process. In general, EAMs assume that information search is a probabilistic process (Bergert & Nosofsky, 2007; Busemeyer & Townsend, 1993; Noguchi & Stewart, 2018) or follows a deterministic search order (Lee & Cummins, 2004; see also Busemeyer et al., 2019). However, evidence from research utilizing eye tracking showed that, while EAMs predictions for attention allocation were largely supported, information acquisition was not stochastic and was influenced by top-down and bottom-up processes (cf. Orquin & Mueller Loose, 2013). In line with that, EAMs cannot inherently explain why top-down influences of the information's consistency have been shown to impact the weighting of information and subsequently choices during the decision process (Glöckner et al., 2010).

Parallel-Constraint Satisfaction Models

The top-down influence of consistency of information on decision-making is modeled explicitly in parallel constraint satisfaction models (Glöckner & Betsch, 2008a; Holyoak & Simon, 1999; Read et al., 1997; Rumelhart & McClelland, 1986). These models assume that decision-makers strive for a coherent representation of the decision-relevant information, that is that the available information clearly supports one option and contradicts the others. Thus, the decision process is interpreted as a coherence-maximization process that stops once a certain level of coherence is achieved. Coherence-maximization is conceptualized as an iterative spread of activation through a neural network representing the decision situation. As a consequence of this coherence-maximization process, parallel constraint satisfaction models predict coherence shifts during decision-making (Glöckner & Betsch, 2008a; Holyoak & Simon, 1999; Montgomery, 1989). That is, decision-makers tend to increase the coherence of a decision situation, for example by overweighting information that is consistent with the emerging favored option or underweighting inconsistent information. Many studies supported the constructive role of coherence during decision-making in the form of coherence shifts (Glöckner, 2008; Glöckner et al., 2010; D. Simon et al., 2008; D. Simon et al., 2004; see also Brownstein, 2003, for a review of biased predecision processing). Parallel constraint satisfaction models additionally predict that information integration can be quick and exhaustive at the same time, in case the decision situation under investigation is coherent (Glöckner & Betsch,

applies to any model that includes parameters that need to be fitted to data.

2008a, 2008b). This prediction is in contrast to multi-strategy accounts that assume that the more information is processed, the longer a decision takes (Gigerenzer & Todd, 1999). Yet, the studies by Glöckner and Betsch (2008b) and Glöckner and Betsch (2012) showed that in coherent decision situations decision-makers were able to integrate all available information quickly and efficiently.

Despite the success of parallel constraint satisfaction models in accounting for decision-making behavior, early implementations of these models were criticized for being underspecified and, thus, too flexible (Marewski, 2010). In response, Glöckner et al. (2014) introduced a fully formalized *parallel constraint satisfaction model of decision making* (PCS-DM) which predicts decisions, decision times, and decision confidence either in a fixed variant without any free parameters or in a version that assumes one free parameter for modeling individual differences in decision-making. From a meta-theoretical perspective, PCS-DM's properties as a theory are comparable to those of EAMs as both models are single-mechanism accounts of decision-making that predict several dependent variables and assume free parameters to explain adaptive decision behavior (Glöckner & Betsch, 2011). In comparison to EAMs and the assumed decision strategies of the multi-strategy accounts, however, PCS-DM still lacks the ability to predict information search (Glöckner et al., 2014; Jekel et al., 2018) and also does not make precise predictions about attention allocation on the cue-value level (Orquin & Mueller Loose, 2013). Due to the importance of information search for the prediction of decision-making (Gigerenzer et al., 2014; Todd & Gigerenzer, 2003), Jekel et al. (2018) extended PCS-DM to the integrated coherence-based decision and search model (iCodes) by formalizing the prediction of coherence-based information search.

1.2 A Model for Coherence-Based Decision-Making and Information Search

With the *integrated coherence-based decision and search model* (iCodes), Jekel et al. (2018) extended PCS-DM's (Glöckner et al., 2014) predictions for choices in probabilistic-inference tasks to also include information search. In this type of tasks, decision-makers have to choose the option out of two (or more) that is most likely to maximize an objective decision criterion based on the given information. The basis of this choice is the probabilistic information provided by cues that differ in their validities. The validity of a cue in this task is the predictive quality of the information and represents the probability of this cue correctly predicting the option with a higher criterion value, given that this cue discriminates (cf. Gigerenzer & Goldstein, 1996). Cues provide information on the likely success of each option (also referred to as cue values) and this information can be either already available or still concealed and searchable. For simplicity, the cue values are binary in many experimental settings, in that they are either positive or negative endorsements of an option (see Figure 1 for an illustration).

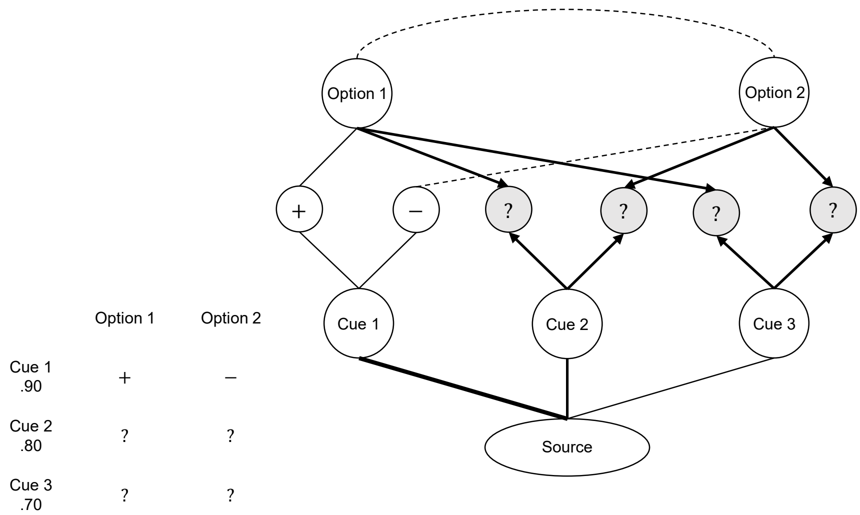

FIGURE 1: iCodes network representing an exemplary decision situation. The information of the decision task on the left is represented in the network on the right. Nodes represent options, cues, and cue values. + indicates a positive evaluation of an option, − a negative evaluation, and ? concealed and searchable information. Cues differ in their respective validities which is represented by relative line thickness in the links that connect the source node to the cue nodes. Links with an arrow head are unidirectional in the direction the arrow points to, all other links are bidirectional. Dotted lines represent inhibitory links that reduce the activation of the associated nodes.

The information of a probabilistic-inference task is the basis for iCodes' network, as it represents all the information in the form of nodes and links connecting the nodes (Jekel et al., 2018). The relevant extension from PCS-DM to iCodes is a layer of cue-value nodes that has been introduced into the network, in addition to the nodes representing the options and the cues (see Figure 1). iCodes still assumes the same iterative spread of activation through the network as PCS-DM as the underlying decision and search process (cf. Glöckner et al., 2014; Jekel et al., 2018).

This spread of activation maximizes the coherence of the decision situation while considering the reciprocal constraints introduced to the network by the decision task (such as contradicting information or being only able to choose one option). Once a coherent representation of the decision situation is achieved, this spread of activation stops and iCodes makes a prediction for choices and information search. In the following, I provide more details on the underlying spread of activation. I, then, describe how predictions for dependent variables of decision-making can be derived from iCodes. Finally, I conclude this chapter by introducing the currently most prominent prediction for information search by iCodes, the attraction search effect.

The Iterative Spread of Activation

The iterative spread of activation is initiated by the source node at the bottom of the network (Jekel et al., 2018, see also Figure 1). From the source node, activation is spread to the options and back to the cue nodes via the bidirectional links connecting cue, cue-value, and option nodes. The spread of activation from the source node to the option nodes and back to the cue nodes constitutes one iteration and is repeated until the levels of activation at each node do not change substantially anymore, indicating a coherent representation of the decision situation.[2] Only nodes representing available cue values contribute to the iterative spread of activation as only these nodes are connected to option and cue nodes via bidirectional links (just as the links between cue and option nodes in PCS-DM, Glöckner et al., 2014). Concealed and, therefore, searchable cue values are connected via unidirectional links that only enable concealed cue-value nodes to receive activation from the option and cue nodes but do not allow them to spread activation back to the other nodes, as they do not carry any information on the options and cues yet (Jekel et al., 2018).

The amount of activation each node receives through the spread of activation depends on the characteristics of the decision situation. The cue nodes receive activation from the source node proportionally to their respective validities (Glöckner et al., 2014; Jekel et al., 2018). The same is true for the activation cue-value nodes receive from the cue nodes. Thus, nodes representing more valid cues and their cue

[2]For the formalization of the spreading-activation mechanism, refer to Jekel et al. (2018), pp. 752.

values receive more activation than nodes representing less valid cues and their cue values. The translation of validity differences to activation differences at the node level is modulated by a free parameter P. This parameter represents the individual sensitivity towards cue-validity differences. High P parameters represent a high sensitivity towards validity differences resulting in more noncompensatory information integration, such that information of less valid cues cannot override information of more valid cues (cf. Payne et al., 1993). In contrast, low P parameters lead to more compensatory information integration, as they represent low sensitivity towards cue-validity differences and thus, information of cues with differing validities is weighted more equally.

The option nodes receive activation from the cue-value nodes that are currently available (i.e. not concealed). The amount of activation option nodes receive depends on the valence of the available cue values and their respective validities: The activation of an option node increases, if the cue values support the respective option and more so if the supporting cue values are more valid. If the cue values contradict an option, the activation of the respective option node is reduced - even more so if the contradicting cue values are highly valid. The option nodes themselves are connected via an inhibitory link. Due to this inhibitory link, the activation of one option is automatically reduced if the other option receives activation from the cue values and vice versa, complying with the demand of the task that only one option can be chosen.

From the option nodes, activation is spread back to the cue-value nodes. The more an option is supported by the already available evidence, the more activation connected cue-value nodes receive. Via the bidirectional links connecting available cue-value nodes and cues, cue nodes also receive activation from the option nodes. Due to these bidirectional links, the weight of cues that support the currently preferred option is increased during the decision process. Both, the inhibitory link between the option nodes and the bidirectional links between cue, available cue-value, and option nodes are constraints within the network that implement coherence principles in the decision process (Glöckner et al., 2014).

The Prediction of Information Search and Decisions

Once the activation levels of the nodes stabilize, that is, once their activation levels do not change substantially anymore between iterations, the iterative spread of activation stops and iCodes' prediction for the decision situation can be derived. iCodes predicts that the option whose node received the most activation at the end of the decision process should be chosen (Glöckner et al., 2014; Jekel et al., 2018). iCodes also predicts that the higher the difference of option nodes' activation-levels, the higher the decision confidence should be. Further, the number of iterations it takes for the network to stabilize predicts the time it takes to make a decision. For the prediction of information search, Jekel et al. (2018) applied the same logic as with the prediction of choices: The concealed cue value, whose node received the most activation (compared to other concealed cue-value nodes) after the network stabilized, is predicted to be searched for.

Note, that all predictions made by iCodes are deterministic in principle. In order to transform iCodes' deterministic predictions to probabilistic predictions[3], Jekel et al. (2018) utilized a softmax choice rule (see also Glöckner et al., 2014). With this choice rule, two additional free parameters are introduced into the model, λ_C and λ_S. Both parameters represent the sensitivity towards the differences in activations, one of the option nodes (λ_C) and the other of the cue-value nodes (λ_S). High λ parameters represent a strong adherence to iCodes' choice and search prediction, while λ parameters of zero represent random choices and information search.

The Attraction Search Effect

iCodes predicts information search based on the amount of activation that concealed cue-value nodes received once the network stabilized. The activation of concealed cue-value nodes is determined by the sum of activation they receive via the unidirectional links from option and cue nodes. As already described above, the activation that stems from the cues is proportional to their respective validities and the activation that stems from the options is proportional to the currently available evidence that supports the option.

Due to these two sources of activation in the model, the following predictions for information search can be derived from iCodes: All else being equal, the concealed cue value from the most valid cue should be searched for. At the same time, and again, all else being equal, the concealed cue value that carries information on

[3]It has been argued that probabilistic predictions for choice are psychologically more plausible (i.e., Hilbig & Moshagen, 2014). Further, transforming deterministic to probabilistic predictions facilitates comparisons of iCodes with other theories that make probabilistic predictions (cf. Glöckner et al., 2012; Glöckner et al., 2014)

the currently attractive option (based on the already available evidence) should be searched for. Thus, iCodes predicts that people should show a tendency to search for new information on the option that is currently supported by the already available information. This prediction has been coined as the *attraction search effect* (ASE) by Jekel et al. (2018) and is unique in the sense that neither EAMs nor any heuristics from the multi-strategy accounts currently predict that information acquisition depends on the already available evidence.

Jekel et al. (2018) investigated the ASE and iCodes in three experiments by utilizing a hypothetical stock-market game in which participants had to choose which of two stocks was going to be more successful based on expert recommendations. The authors manipulated the attractiveness of the options by designing two versions of cue-value patterns. These patterns differed in the option that was supported by the already available evidence. The main focus of the experiments was to find evidence for the ASE. For this purpose, the authors created an index, the *attraction search score* (ASS), that is the difference of the relative frequency of searching information for one option given that this option is attractive minus the relative frequency of searching for information on the same option given that this option is unattractive, $ASS = p(search_{Opt1}|Opt1\ attractive) - p(search_{Opt1}|Opt2\ attractive)$. If the ASS was positive, participants' search behavior was in line with the ASE and the predictions of iCodes.

The experiments provided support for iCodes' predictions by showing that participants' ASS was positive on average. Thus, participants showed a tendency to search new information for the option that was currently supported by the evidence. This tendency persisted when information search was restricted to one additional piece of information, unrestricted but costly in that participants had to pay for each information they searched, or unrestricted and free. The type of information search, however, moderated the size of the ASE, such that the strongest ASE was shown for restricted search and the ASE was weakest but still significant for free search. Next to the behavioral results, iCodes performed also well as a computational model in predicting choice and search behavior compared to selected strategies from the adaptive toolbox. The modeling results further emphasized the importance for including coherence processes in the prediction of information search. Overall, Jekel et al. (2018) introduced a new and formalized model for coherence-based decision-making and search and provided initial evidence for the ASE specifically and iCodes more generally.

1.3 iCodes as a Theory of Coherence-Based Decisions and Search

In light of the replication crisis in psychology (Open Science Collaboration, 2015), there have been calls for more well-specified and ideally formalized theories in psychology (Glöckner & Betsch, 2011; Glöckner et al., 2018; Smaldino, 2019). In their article, Glöckner and Betsch (2011) suggested assessing the empirical content of theories in JDM in order to advance theory development and facilitate critical testing of theories. According to Popper (1935), the empirical content of theories represents their degree of falsifiability or, in other words, the "amount of information [theories] convey concerning the world" (Glöckner & Betsch, 2011, p.711).[4] The higher the degree of falsifiability of a theory, the more observations its predictions forbid and the higher its empirical content. To assess the empirical content of theories, Popper (1935) proposed to evaluate their level of universality and their degree of precision. A theory's level of universality is determined by the number of situations to which its predictions can be applied (Glöckner & Betsch, 2011). If a theory's predictions have a large scope of application, such that they apply to many different tasks, contexts, or individuals, the level of universality of this theory is higher than a theory with only a few areas of application. On the other hand, a theory's degree of precision refers to "how much a theory forbids in the situations to which it can be applied" (Glöckner & Betsch, 2011, p. 711). That is, the degree of precision of a theory is higher, if it makes more precise predictions than other theories for the same situation. For instance, if a theory predicts that either behavior x or behavior y should occur in a certain situation, its prediction is less precise compared to a theory that predicts that behavior x and only this behavior should occur in the same situation. Both, the level of universality and the degree of precision of a theory independently contribute to a theory's empirical content; if both are high, its empirical content is high.

The empirical content of a theory enables its evaluation even prior to empirical testing (Glöckner & Betsch, 2011). If the empirical content of a theory is high, it makes precise predictions for many different situations, can be tested critically

[4]In this thesis, I use the notion of theories' empirical content merely as a tool to evaluate and compare theories as well as to identify areas for future research. I, therefore, refrain from a critical discussion of Popper's philosophical theory of science as a whole or its relation to other streams in the philosophy of science.

and be potentially falsified. Due to the higher degree of falsifiability, theories also contribute more to the advancement of science if their empirical content exceeds those of other theories. This scientific advantage even holds if a theory outperforms other theories in only one aspect of empirical content, but only if this aspect is corroborated empirically (cf. Glöckner & Betsch, 2011). The goal of this thesis is to evaluate and critically test iCodes' properties as a theory and its contribution to the advancement of the field of JDM.

To assess iCodes' level of universality, one has to examine to which situations iCodes' predictions can be applied. iCodes applies to any decision situations in which one option has to be chosen among others based on the information provided by attributes of these options. Compared to PCS-DM, iCodes has a higher level of universality, since it can also be applied to situations in which information has to be searched for. To date, however, all empirical investigations of iCodes utilized probabilistic-inference tasks presented as hypothetical stock-market games. It is, therefore, an open question whether iCodes' predictions are also applicable to other types of multiple-cue judgment tasks, for instance preferential choice. The investigation of iCodes' scope of applicability is an important step for evaluating iCodes' merit as a theory. If iCodes' predictions only applied to a specific task or paradigm, the added value of iCodes would be negligible. My co-authors and I, therefore, tested iCodes' level of universality in the first manuscript by assessing whether its predictions for information search apply, independent of characteristics of the decision task. Specifically, I investigated in three experiments whether the attraction search effect generalized to different decision contexts. Providing support for the generalizability of the attraction search effect would bolster iCodes' relevance for the field of JDM.

Next to the level of universality, it is also important to assess iCodes' degree of precision. As a fully-formalized theory, iCodes already makes very precise predictions for information search and choices that depend on task characteristics, for instance the already available evidence or the validity of cues. An additional aspect of a theory's precision is the a priori prediction of potential boundary conditions. Detailing under which circumstances changes in the originally predicted behavior should be observable, increases the specificity and, thus, the degree of precision of a theory. One potential, model-inherent boundary condition of iCodes is that decision-makers might differ in their relative strength of the option-attractiveness influence on search. In the current formalization of iCodes, the strength of the option-attractiveness influence is fixed, representing the assumption that the influence of validity on information search is ten times stronger than the influence of option-attractiveness (cf. Jekel et al., 2018). It is, however, reasonable to assume that this ratio differs between individuals and situations, for example because the awareness of differences in option attractiveness varies. In Manuscript II, my co-authors and I therefore tested a manipulation that should increase the strength of the option-attractiveness influence on search and, thus, the size of the attraction search effect. Showing that a theoretically motivated moderator influences iCodes' predictions, would support iCodes as a precise and strong theory of information search. In addition, by capturing variance in the option-attractiveness influence on search with a model-inherent parameter, I aim to validate iCodes' assumed information-search process.

Another property of theories with high empirical content is the prediction of multiple dependent variables (Glöckner & Betsch, 2011). On the one hand, multiple dependent variables increase the level of universality of a theory, as this theory can make predictions in situations that require different types of dependent variables. On the other hand, multiple dependent variables can also increase the degree of precision of a theory, by specifying a pattern of different outcomes and behaviors that should occur simultaneously. Predicting such a pattern of behaviors increases the number of observations that would falsify the theory and, therefore, increases the theory's degree of precision. Next to information search and process measures already predicted by PCS-DM, iCodes also predicts attention allocation in multiple-cue judgment tasks. Specifically, it predicts that the coherence of information should influence the distribution and the temporal development of fixation behavior. Thus, iCodes is an answer to Orquin and Mueller Loose (2013) who called for more specified theories that account for attention allocation during decision-making. Showing that iCodes' predictions for information search are also applicable to purely visual search would widen iCodes' scope of application to less structured and more naturalistic settings. Therefore, my co-authors and I empirically tested iCodes' level of universality by investigating its predictions for attention allocation in decision tasks with open information displays in Manuscript III. In two experiments, I assessed the role of coherence for fixation behavior during information search and decision-making. Providing support for the coherence influence on eye movements in decision tasks would enhance iCodes' contribution to research in JDM by underlining the importance of information consistency in decision-making and information search.

Each manuscript presented in my thesis investigates one aspect of iCodes as a theory of coherence-based decision-making and search. Further, each manuscript sheds light on the importance of coherence of information during search. Therefore, this thesis not only adds to the theoretical development of iCodes and JDM but also provides further insights into the underlying cognitive processes during information search. In the following chapter, I summarize the three manuscripts and present their core results (the full manuscripts can be found in Appendix D).

2 Testing and Validating iCodes

In three manuscripts, we tested the predictions of iCodes for information search. Specifically, we tested the generalizability of the attraction search effect in Manuscript I, boundary conditions of the emergence of the attraction search effect in Manuscript II, and the applicability of iCodes' predictions to attention allocation in Manuscript III. By critically investigating iCodes, we evaluated the degree of precision and level of universality empirically.

2.1 The Generalizability of the Attraction Search Effect

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488-512.

Following the introduction of iCodes, Jekel et al. (2018) demonstrated with the attraction search effect (ASE) a new pattern of information-search behavior that could not be accounted for by other current theories in JDM. As iCodes was introduced as a general theory of (coherence-based) decision-making and search, it is important to assess the scope of application of its unique predictions: If the ASE appeared only in specific experimental designs, iCodes would predict a pattern of information search only for a specific task. As a consequence, the added value of iCodes and its predictions would be negligible and iCodes would not bear any theoretical advantage (Glöckner & Betsch, 2011).

In the first manuscript we, therefore, tested the generalizability of the ASE by conducting conceptual replications that systematically vary the characteristics of the decision task. The benefit of such conceptual replications is that they not only test the robustness of iCodes' predictions but also increase the confidence that the observed behavior is due to the assumed underlying cognitive processes and not a by-product of task characteristics of the original experiments (Bredenkamp, 1980).

All previous experiments investigating the ASE employed the same probabilistic-inference task as a hypothetical stock-market game, which was presented in the same matrix-format, and utilized the same constellations of available and concealed cue values (also referred to as cue-value patterns; Jekel et al., 2018). All these experimental-design choices increased the chances to find evidence for the ASE: The hypothetical stock-market game allowed full experimental control over characteristics of the decision task (such as cue validities; Bröder, 2000, 2003), the matrix set-up was shown to be conducive for the predictions of parallel constraint satisfaction models (Söllner et al., 2013), and the constellation of already available information in the cue-value patterns was specifically designed to maximize the likelihood of finding the ASE (Jekel et al., 2018).

To test the generalizability of the ASE, we varied these three aspects (semantic context, cue-value patterns, presentation format) of the decision tasks in three experiments. Our main dependent variable of interest was the attraction search score, an index of information search. As already stated before, this index represents the difference of the probabilities of showing behavior consistent with the ASE and behavior inconsistent with the ASE, $ASS = p(search\ consistent\ with\ ASE) - p(search\ inconsistent\ with\ ASE)$. We considered a replication successful, if the ASS was on average positive, that is, if participants showed more consistent than inconsistent search behavior with the ASE.

In the first experiment ($N = 303$), we changed only the semantic setting of the information-search task by replacing the hypothetical stock-market game with six different scenarios, such as choosing a hotel or picking a trip destination based on a weather forecast. We continued to use a subset of the diagnostic cue-value patterns from Jekel et al. (2018) and restricted participants' search to one piece of information.

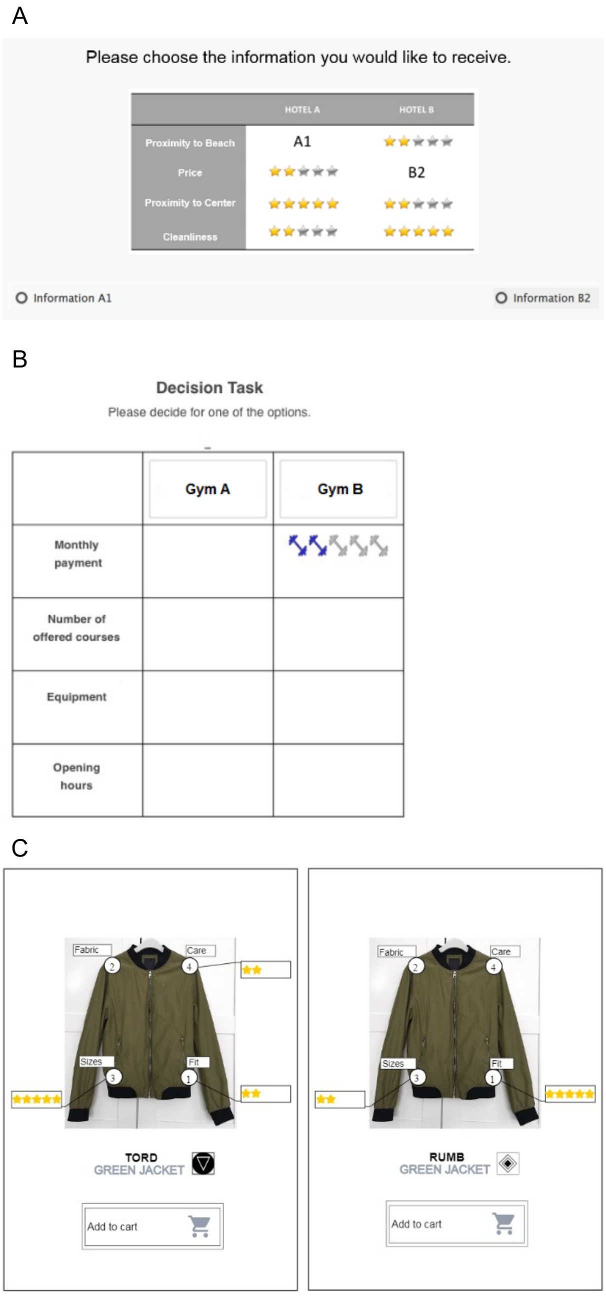

FIGURE 2: Examples of the experimental displays used by Scharf et al. (2019), all translated from German. In Experiment 1 (Figure 2 A), participants could search for one additional piece of information by indicating their search on a scale underneath the task. Information search was operationalized by clicking in the empty table cells in Experiment 2 (Figure 2 B). In Experiment 3 (Figure 2 C), participants could search for information by clicking on the numbers indicating the different attributes of the item of clothing.

In the second, preregistered experiment ($N = 297$), we extended the six decision scenarios by six additional, new semantic contexts. In addition, we switched from diagnostic, half-opened cue-value patterns to a task set-up in which all information was concealed at the beginning of each trial. To control the attractiveness of options, we manipulated whether the first opened cue value was positive (making the first searched-for option attractive) or negative (making the first searched-for option unattractive), independent of which cue value was opened first. The valence of the remaining cue values was randomized. Information search in this experiment was also restricted in that participants could inspect either three, five, or seven pieces of information per trial.

In the last, preregistered experiment ($N = 99$), we returned to the original cue-value patterns from Jekel et al. (2018) but presented them in a semi-realistic online-shop context (see Figure 2 for the experimental displays of all three experiments). This online-shop scenario avoided the classical matrix presentation of the previous experiments, which was shown to influence information-search behavior (cf. Bettman & Kakkar, 1977; Ettlin et al., 2015). Just as in Experiment 1, information search was restricted to one piece of information.

The results of all three experiments broadly supported the generalizability of the ASE, in that the average ASS was positive in all three experiments (see Figure 3 for the average ASS of each experiment). Thus, in all experiments, participants showed a tendency to search for new information for the option that was currently supported by the available evidence. The size of the ASE varied between experiments: While Experiment 1 and 2 both yielded a Cohen's $d = 0.84$, the effect size in Experiment 2 was notably smaller with a Cohen's $d = 0.41$. Analyses using generalized linear mixed models revealed an increase in the inter-individual variability of the information-search behavior as a potential explanation for the differences in effect sizes. One reason for this increase in variability could be the less restrictive information-search implementation in Experiment 2 compared to Experiment 1 and 3 (cf. effect of restrictions of information search in Jekel et al., 2018). Additionally, the change from half-open cue-value patterns to completely closed and random cue-value patterns might have left more room for pre-determined search strategies to take effect and, thus, increased variance in information search. The effect size of the ASE was also considerably reduced compared to Jekel et al.'s (2018) original studies, which illuminated that the previously used, controlled experimental settings were indeed conducive to finding the ASE (see Figure 3).

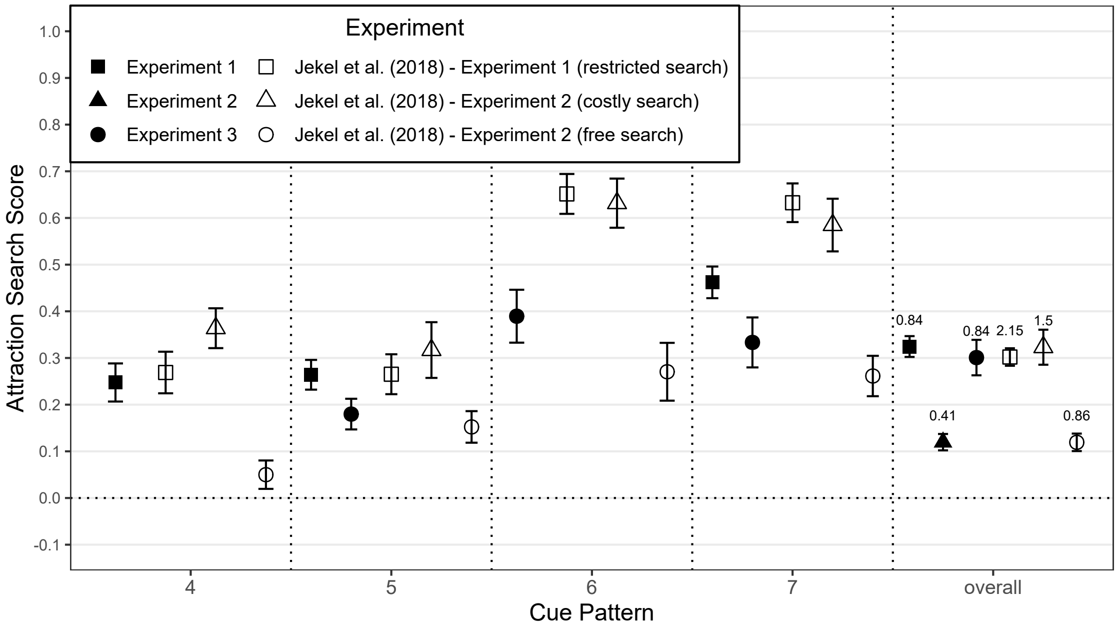

FIGURE 3: Mean attraction search scores (ASS) per cue-value pattern and overall for the three experiments reported in Scharf et al. (2019) and the two experiments by Jekel et al. (2018). A positive ASS represents information-search behavior that is consistent with the attraction search effect. Error bars represent the standard errors of the mean. The cue patterns on the x-axis represent the cue patterns as reported in Jekel et al. (2018), Patterns 4, 5, and 7 correspond to Patterns 1, 2, and 3 in Experiment 1, respectively, and Patterns 5, 6, and 7 to Patterns 1, 2, and 3 in Experiment 3, respectively, reported in Scharf et al. (2019). The numbers above the error bars for the overall ASS indicate the effect size (Cohen's d).

The results of Manuscript I emphasized the robustness of the ASE and corroborated the generalizability of iCodes' predictions. Yet, they also highlighted the role of task characteristics for the absolute size of the ASE. Specifically, the results suggested that the ASE is reduced, if information search was less restrictive and if all information was concealed at the beginning of a trial. Furthermore, the data revealed the existence of individual variability in the ASE. Thus, while the ASE was a pervasive phenomenon of information search, the results also highlighted that there are underlying moderators of attractiveness-biased information search.

2.2 Situation, Person, and Task-Specific Variation of the Attraction Search Effect

Scharf, S. E., Jekel, M., & Glöckner, A. (2021). *Testing an extension of the iCodes model to account for situation, person, and task specific variation in the attraction search effect.* Manuscript submitted for publication.

While the results of the first manuscript strengthened the robustness of iCodes' core prediction, they also uncovered substantial variation in the individual and situational variance of the ASE (Scharf et al., 2019). These findings were in line with the results from Jekel et al. (2018) who also showed variability in the ASE between subjects. One potential explanation iCodes offers for this variability is that the strength of the option-attractiveness influence on search differed between situations and/or individuals, for example due to varying preferences for relying on cue validities during information search. Within iCodes, the change of the option-attractiveness influence can be modeled by adjusting the weights of the links connecting option and concealed cue-value nodes and, thereby, adjusting the amount of activation cue-value nodes receive from option nodes. The current manuscript, therefore, tested a theoretically motivated moderator of the ASE by manipulating whether participants had to rate option attractiveness before search. We further examined whether iCodes was able to capture the effect of this moderator with a model parameter, γ, that represents the relative influence of option attractiveness on information search. Showing that iCodes makes precise predictions for the boundary conditions of the strength of the ASE, corroborates iCodes' degree of precision. Further, the ability to capture the effect of a moderator within the existing model structure would strengthen the assumed information-search process of iCodes and validate the model.

To test our assumption that differences in the strength of the ASE are due to changes in the weighting of option attractiveness, we conducted a pre-registered experiment (N = 202) using the original tasks from Jekel et al. (2018) with unrestricted, but costly information search (i.e. participants had to spend a small amount per information search, cf. Experiment 2 in Jekel et al., 2018). We manipulated between subjects whether participants had to rate option attractiveness before information search. Asking participants for attractiveness ratings as a manipulation was used in past research to increase participants' tendency to search for information that supports their currently preferred choice (cf. Fraser-Mackenzie & Dror, 2009). We assumed that pre-search attractiveness ratings increase participants' awareness of option attractiveness and, thus, strengthen its influence on information search. Therefore, we expected that participants in the attractiveness-rating condition show information-search behavior more in line with the ASE than participants in the control condition. Further, we expected that the influence of attractiveness ratings on search varies between cue-value patterns depending on the coherence of the already available evidence in these cue-value patterns.

When the influence of option-attractiveness on information search increases, the nodes representing concealed cue values in iCodes' network should receive relatively more activation from the option nodes compared to the activation from the cue nodes. The amount of activation the nodes receive is determined by the weights of the links connecting them to other nodes. To test whether attractiveness ratings change the amount of activation the option nodes spread to concealed cue-value nodes, we freely estimated the formerly fixed mixture parameter γ. This parameter changes the amount of activation received from option nodes by adjusting the weight of the links connecting (concealed) cue-value nodes and option nodes.[5] In the original iCodes, γ was fixed such that the validity influence on search was ten times stronger than the option-attractiveness influence. If attractiveness ratings increase the influence of option attractiveness on search, we would expect that the individually fitted γ parameters in the condition with attractiveness ratings are larger than in the control condition.

The results showed that rating option attractiveness before search increased the size of the ASE such that participants were more likely to search for information on the attractive option. Hence, iCodes' prediction was corroborated. This effect of attractiveness ratings was also mirrored in the size of the individual γ parameters that were on average larger in the condition with ratings compared to the control condition. Nonetheless, the influence of option attractiveness on search was approximately ten times weaker than the influence of cue validity.

[5] We introduced the γ parameter as mixture parameter that adjusts the weights of option-cue-value links relative to cue-cue-value links. Specifically, the weight of links connecting options and concealed cue values is determined by the product of the weight of links connecting cues and concealed cue values and the odds of γ, $w_{OptCV} = w_{CueCV} * \frac{\gamma}{1-\gamma}$. We fixed γ to a maximum value of 0.5, implying that the influence of option attractiveness could only be equally strong as the cue-validity influence and never stronger.

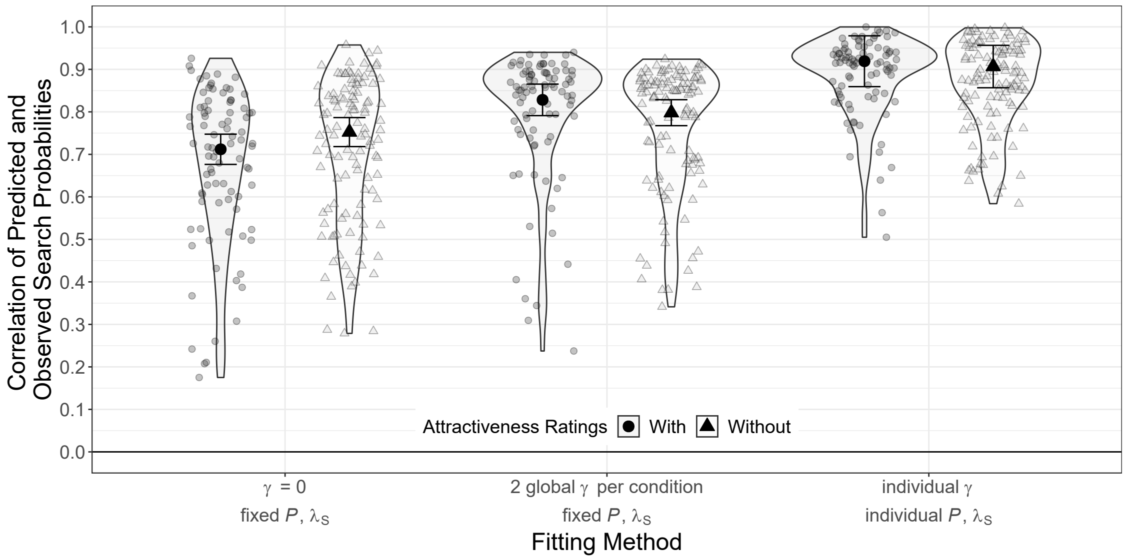

FIGURE 4: Individual Pearson correlations of predicted and observed search probabilities for each condition (dark grey points = attractiveness ratings; light grey triangles = no attractiveness ratings) based on different model parameters. The black dots and triangles are the mean correlation, error bars denote the standard errors of the mean. The model on the left based its predictions on $\gamma = 0$ and fixed P ($= 1.66$) and λ_S ($= 20.18$) parameters, thus, removing the option attractiveness influence on concealed cue-value nodes. The model in the middle fitted a global γ parameter for each condition based on the information-search behavior of all participants in each condition. Finally, the model on the right estimated all parameters for each participant individually.

We compared the predictive performance of different versions of iCodes to further assess the relevance of option-attractiveness influences during search and its role in explaining individual variability of information-search behavior. Specifically, we compared a model with no option-attractiveness influence on search (i.e., $\gamma = 0$) to a model with an influence of the option-attractiveness on search (i.e., $\gamma \neq 0$) which assumed this influence was equal between participants (i.e., one γ parameter fitted per condition). In a second step, we compared these models with a model that allowed for inter-individual differences in the option-attractiveness influence on search (i.e., individual γ parameters). To evaluate the predictive performance of each version of iCodes, we predicted the search probabilities for the concealed cue values and correlated them with the observed search frequencies of the respective cue values. We compared their respective model fit using likelihood-ratio tests. The results of this analysis showed that accounting for an option-attractiveness influence on search as well as accounting for inter-individual differences in this influence improved model fit and predictive performance of iCodes (see Figure 4). In addition to the inter-individual variance in information-search behavior, the results also supported that attractiveness ratings affected cue-value patterns differently, highlighting the role of the already available evidence for the prediction of search. (Supplemental) modeling results further supported the validity of underlying process assumptions of iCodes by showing that the experimental manipulation did not affect the individual P and λ_S parameters.

Overall, this manuscript showed that iCodes can predict the effect of a theoretically motivated moderator and capture its effect with an already existing model parameter. It further highlighted the importance of option attractiveness in predicting information search. These results emphasized the high degree of precision of iCodes and validated its assumed information-search process as well as the role of coherence in information search.

2.3 Predicting Coherence-Based Attention Allocation During Information Search

Scharf, S. E., Bröder, A., Jekel, M., & Glöckner, A. (2021). *Coherence influences on attention allocation and visual information search in decisions with open information displays.* Manuscript submitted for publication.

The results of Manuscripts I and II provided support for iCodes' level of universality and its degree of precision. Another aspect of theories with high empirical content is the prediction of multiple dependent variables (Glöckner & Betsch, 2011). With the extension of a network layer that represents cue values, iCodes is not only able to predict information search but also makes predictions for gaze behavior on the cue-value level. The underlying assumption behind the prediction of gaze behavior is that the activation of the cue-value nodes can be translated into the relative frequency of fixating the respective cue values. This allows iCodes to achieve a high resolution in its predictions for gaze behavior. Thus, iCodes provides an answer to the call of Orquin and Mueller Loose (2013) for more formalized theories in JDM that can account for attention allocation during decision-making. Further, the prediction of attention allocation widens the scope of application of iCodes, since its predictions for information search can now be applied to situations without active (behavioral) search.[6] Therefore, by deriving and testing iCodes' predictions for visual information search, we empirically evaluated iCodes' level of universality as well as the role of coherence in gaze behavior during decision-making.

Assuming that the activation of cue-value nodes translates to relative fixation frequencies of these cue values, the following qualitative predictions for attention allocation can be derived from iCodes: First of all, just as iCodes predicts that information should be searched for first on the attractive option, it also predicts that new information on the attractive option should be fixated first. We coined this prediction the *attraction attention effect*. Further, iCodes predicts that coherent information should be fixated more than incoherent information, a prediction we coined the *coherence attention effect*. This prediction stems from the influence of option attractiveness on cue-value node activations, as cue values supporting the attractive option should receive more activation from the option nodes than contradicting cue values.

Looking more closely at the temporal development of the iterative spread of activation, we deduced that the fixation pattern should change over the course of a trial: As the validity of information is the first influence on cue-value nodes activation, we expect that, at the beginning of a trial, fixations should be mainly determined by cue validity. Thus, we would expect that more valid cues are fixated more at the beginning of a trial compared to less valid cues. As the influence of option attractiveness on cue-value node activations occurs later during the spread of activation, we expect the influence of coherence on fixation behavior to take effect only later in a trial. At the same time, we expect the strength of the validity influence on fixation behavior to decrease towards the end of a trial. Taken together, we expect that in the beginning of a trial fixation behavior is mainly influenced by the validity of information while towards the end of a trial the coherence of information becomes a more important determinant. We subsumed these time-course predictions of iCodes for fixations under the name *late coherence effect*. Finally, iCodes also predicts that information on the subsequently chosen option should be fixated more towards the end of a trial - corresponding to the gaze cascade effect that is also predicted by evidence accumulation models (first introduced by Shimojo et al., 2003; Krajbich et al., 2010; Krajbich et al., 2012).

[6]Note, that it also increases the precision, since iCodes simultaneously predicts several dependent variables such as active information search, gaze behavior, information search times, and decisions. As we solely tested iCodes' predictions for visual search in open information displays, however, the main focus in this manuscript is the level of universality of iCodes' predictions.

To test iCodes' predictions for attention allocation, we ran two experiments using hypothetical stock-market games. In the first experiment ($N = 57$), we focused on testing whether new information was fixated first when it described the favored option by implementing a two-stage experimental design: In the first stage, participants were presented with decision situations in which the information of one cue was still concealed. In this stage, they had to rate which option was more attractive based on the already available information. The first stage was introduced to increase the effects of option attractiveness on search. The information of the concealed cue was then revealed in the second stage of the experiment, in which participants had to choose the stock they deemed more successful. The results showed strong support for the prediction that participants fixated new information on the currently attractive option first and, thus, replicated the findings for behavioral information search with gaze patterns. Further, participants in general were more likely to fixate coherent information than incoherent information. To assess the temporal development of gaze behavior, we binned the fixations in each trial into two bins of equal duration. With regard to the prediction of the change in fixation behavior over the course of a trial, the results supported a stronger influence of cue validity on fixation behavior in the beginning of a trial than towards the end of a trial. Yet, there was no support that the coherence influence on fixation behavior indeed increased over time in Experiment 1 when comparing the first and the second half of the trial (see Figure 5 for a visualization of the coherence-influence on fixations across a trial in both experiments). The tendency to fixate information on the subsequently chosen option, however, increased over the course of a trial, replicating the aforementioned gaze-cascade effect.

While the design of Experiment 1 increased the chances of finding an ASE for fixations, it introduced confounds to the fixation behavior: With the two-stage design, we artificially split the information-integration process, which complicated for which stage the prediction of the temporal development of fixation behavior should be applied. Further, the display of the information in the decision task confounded the interpretation of the validity influence on fixation behavior, as the cues were ordered by validities and not equi-distant from the inter-trial fixation cross. To more closely investigate the temporal development of fixations within a trial, we ran Experiment 2 ($N = 50$), which dropped the rating phase and explicitly manipulated the coherence of two cues. Again, we binned fixations into two bins of equal duration. In this experiment, we varied the order of cues and presented the cue values

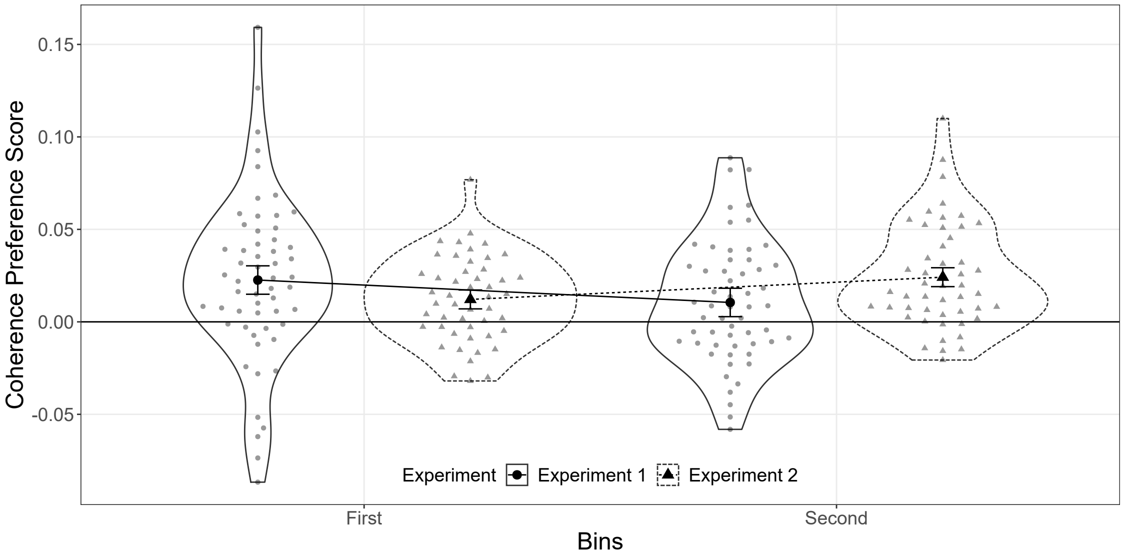

FIGURE 5: Individual and mean coherence preference scores (CPS) per time bin and experiment (dots and solid lines represent Experiment 1, triangles and dotted lines Experiment 2). Error bars represent the standard error of the mean. The CPS is calculated as the difference of the relative frequency of fixating coherent information and the expected random probability of fixating coherent information, $CPS = p(fix_{coherent}) - \frac{n_{coherentCVs}}{total\ n_{CVs}}$. If the CPS is larger than zero, participants were more likely to fixate coherent information than chance level. According to iCodes the CPS should be larger than zero overall (= coherence attention effect) and increase from the first bin (first half of a trial) to the second bin (second half of a trial).

on a circle around the inter-trial fixation cross.

The results of Experiment 2 also showed strong support for the predictions that participants fixated new information on the currently attractive option first and were in general more likely to fixate coherent information than incoherent information. In Experiment 2, there was only weak support that the coherence influence on fixation behavior increased over time. Just as in Experiment 1, Experiment 2 also replicated the gaze-cascade effect. (Supplemental) modeling results for both experiments further showed that the relative frequency of fixating cue values was positively correlated with the activation-levels at the cue-value nodes, which supported the assumption that these levels of activation can be used as a proxy for the relative number of fixations per cue value.

In summary, the results supported the role of coherence for attention allocation and information search: Participants' fixations were guided by the coherence of information, both for newly revealed information and across all displayed information. While the prediction for the time-course of the coherence influence on fixations was not fully supported, they highlighted the benefits of formalized models of decision-making: iCodes allowed for testing these fine-grained predictions of fixation behavior and thereby enabled the identification of new patterns of attention allocation. Further, in showing that coherence influences fixation behavior, the results emphasized that iCodes provides a unique contribution to the JDM literature.

3 General Discussion

In my thesis, I evaluate iCodes as a theory of coherence-based decision-making and search. I thereby aim to advance iCodes as a theory, by specifying its predictions and assessing whether they are corroborated by data. In addition, I hope to add to the development of theories in JDM in general by demonstrating the importance of coherence for decision and information-search processes and emphasizing the advantages of formalized models of decision-making. With three manuscripts that employed conceptual replications, computational modeling, and process-tracing measures, I critically tested the theoretical properties of iCodes.

In Manuscript I, my co-authors and I showed that iCodes' seminal prediction of the attraction search effect generalized to decision tasks with different cue-value patterns, different semantic contexts, and different presentation formats. The results also validated the underlying process assumptions of iCodes by showing that the tendency to search for information regarding the currently attractive option was not a by-product of specific task characteristics. As a whole, Manuscript I supported the universality of iCodes' information search predictions by demonstrating the robustness of the attraction search effect.

The second manuscript presented evidence that the attraction search effect was stronger when participants rated option attractiveness before search. The effect of attractiveness ratings on search was theoretically motivated within iCodes by postulating that the awareness of option attractiveness increased its weight in the information-search process. This proposed underlying mechanism was supported by the evidence that the model-inherent γ parameter was sensitive to the attractiveness-rating manipulation. The results of Manuscript II emphasized the precision of iCodes' predictions by providing support for a theoretically motivated moderator. Additionally, the results validated the role of the option-attractiveness influence on information search.

Finally, in Manuscript III, we tested iCodes' predictions concerning an additional dependent variable, namely attention allocation. The experiments in Manuscript III showed that there was a preference for fixating coherent information, however, there was only weak support for the predicted change in this preference over the course of a trial. The results, firstly, underlined the importance of accounting for coherence when predicting fixation behavior specifically, and predicting information search in general. They also showed that formalized theories allow for precise tests of the underlying processes of information search and can uncover previously unnoticed details about the information-search process. The manuscript further provided evidence for the scope of application of iCodes by showing that its information-search predictions can also be applied to visual search in open information displays.

Taken together, the evidence presented in the manuscripts supported iCodes' predictions to a large extent. To derive conclusions regarding the merits of iCodes as a theory, one has to integrate the results and evaluate them and their relation to other theories in JDM. In the following, I assess the theoretical properties of iCodes based on the results presented in the manuscripts and in comparison to the multi-strategy accounts and evidence-accumulation models in JDM. For this analysis, I again utilize the criteria for evaluating the empirical content of theories proposed by Popper (1935).

3.1 Evaluation of iCodes' Theoretical Properties

When new theories are introduced, it is important to explore their contribution to the theoretical landscape of the field. The formulation of precise and, therefore, falsifiable theories is an important step for the progress of research in psychology (Glöckner & Betsch, 2011; Glöckner et al., 2018). In addition, a theory also has to withstand empirical tests to be regarded as advantageous for the field (Popper, 1935). In the following, I first evaluate iCodes' level of universality based on the evidence put forward in Manuscript I and III and in comparison to other theories in JDM. In a second step, I repeat this evaluation for iCodes' degree of precision based on the evidence put forward in Manuscript II.

The Level of Universality of iCodes

A theory's level of universality refers to its scope of application: To how many situations are its predictions applicable (Glöckner & Betsch, 2011; Popper, 1935)? The more situations a theory can be applied to, the higher its level of universality. To assess iCodes' level of universality, one, therefore, has to compare its scope of application with other theories in JDM. iCodes' predictions can generally be applied to multi-cue decision tasks, that is, to any tasks in which a decision has to be made between options based on information provided by (binary) cues of varying diagnosticity. While the previous evidence presented for iCodes was fairly restricted in the task design (cf. Jekel et al., 2018), Manuscript I tested different variants of multi-cue decision tasks. The results supported iCodes' predictions independent of the employed task design. In comparison to earlier versions of parallel-constraint satisfaction models, iCodes' level of universality increased as the ability to predict information search allowed its application to decision tasks with completely or partially concealed information. Manuscript III further supported iCodes' level of universality by showing that its predictions for information search can also be applied to multi-cue judgment tasks with open information displays that require visual search. Therefore, with the extension to predict information search in terms of visual and behavioral search, iCodes' level of universality matches that of EAMs as well as multi-strategy accounts of multi-cue judgment tasks, since both theoretical approaches also predict visual and behavioral search for this type of task.

However, many different types of decisions are investigated in JDM (cf. Goldstein & Hogarth, 1997). A universal theory of decision-making should ideally be applicable to any situation in which a decision is made, regardless of the specifics of the task at hand. For example, in sequential decision-making participants have to sample an option, evaluate its value regarding the choice criterion, and subsequently decide whether they want to continue sampling (T. S. Ferguson, 1989; Seale & Rapoport, 1997). EAMs can be easily adapted to account for this type of task by assuming that the threshold represents the decision to stop sampling options (cf. Busemeyer & Townsend, 1993, for an implementation). The same applies to multi-strategy accounts of decision-making that can include strategies for the sequential decision-making paradigm (cf. Pitz et al., 1969; Saad & Russo, 1996; see Todd & Gigerenzer, 2003, for an overview). For instance, a simple heuristic for this type of task is the cut-off rule that predicts that decision-makers sample n options, and then select the next option that is better than all previously sampled alternatives (cf. Seale & Rapoport, 1997). In its current implementation, iCodes cannot be applied to these tasks without introducing additional assumptions in order to predict when information sampling stops. Similarly, further assumptions are necessary to use iCodes for predicting decisions from experience, a sub-paradigm of risky choice in which information about gambles is sampled freely (Hertwig et al., 2004). Again, both EAMs and heuristics have been applied to this type of decision (for an example of EAMs, see Leuker et al., 2019; for heuristics, see Hau et al., 2008).

Taken together, this analysis suggests that the level of universality of iCodes is reduced compared to that of EAMs and multi-strategy accounts. Both theoretical accounts can be applied to a broader variety of decision tasks than iCodes.[7] It is important to note, however, that the above analysis of the level of universality compared a single, new theory to broadly developed theoretical accounts. Future developments of iCodes, therefore, have the potential to increase its level of universality.

The Degree of Precision of iCodes

A theory's degree of precision refers to the specificity of its predictions (Glöckner & Betsch, 2011; Popper, 1935): The more behavior a theory forbids in a given situation, the more precise are its predictions and the higher is its degree of precision. For instance, a theory makes more precise predictions compared to other theories, if it predicts more dependent variables simultaneously in one given situation (Glöckner & Betsch, 2011). Next to information search and attention allocation, iCodes predicts several dependent variables such as choices, decision times, and choice-confidence judgments. These dependent variables are also predicted by PCS-DM (Glöckner et al., 2014), EAMs (Busemeyer & Diederich, 2002; Hausmann & Läge, 2008), and multi-strategy accounts (Glöckner, 2009). A unique property of iCodes is that the prediction for decision confidence and decision times can be translated to information search, such that iCodes predicts information-search times as well as

[7] To (at least) some extent, the universality of multi-strategy accounts stems from features that bear the risk of simultaneously reducing their precision: If the applicability to various tasks and contexts stems solely from adding ad-hoc decision strategies (i.e., the *strategy sprawl problem*; Scheibehenne et al., 2013) or is a result of underspecified selection criteria between the included strategies, the degree of precision of multi-strategy accounts may decrease drastically (Glöckner & Betsch, 2011; Marewski et al., 2018).

information-search confidence. None of the current implementations of EAMs and the multi-strategy accounts predict these dependent variables. Therefore, iCodes predicts more dependent variables simultaneously for a given decision situation compared to both theoretical approaches and, thus, makes more precise predictions.

A unique contribution of iCodes lies in the predicted influence of option attractiveness on information search that can also be extended to the aforementioned dependent variables. By postulating that option attractiveness influences search in addition to cue validity, iCodes makes more precise predictions for information search than theories that assume that cue-validity alone influences search. The results of Manuscript II further supported iCodes' degree of precision by showing that iCodes not only predicts that option attractiveness influences search but also under which circumstances this influence should de- or increase. Both EAMs and multi-strategy accounts would currently require additional assumptions to be able to predict top-down coherence effects on information search. While these theories cannot account for the option-attractiveness influence on search, Jekel et al. (2018) were not the first to describe this pattern of information search: DeKay et al. (2011) and DeKay et al. (2014), for example, showed similar search behavior in risky and preferential choice. While this stream of research also identified striving for consistency as a relevant driver of this information-search behavior (Russo et al., 2008) and suggested that connectionist models might explain it (DeKay, 2015), these findings and theoretical considerations have not yet been embedded in a larger, specified theoretical framework. Thus, iCodes still holds a unique advantage as a fully-formalized model that makes precise predictions about the antecedents, boundary conditions, and extent of the attractiveness influence on search.

Thus, iCodes' predictions for information search are more precise than those of other theoretical accounts. In addition, it makes new predictions about the coherence influence on search that other theories cannot account for, which further increases its degree of precision as a theory (Glöckner & Betsch, 2011). Therefore, the overall degree of precision of iCodes is higher than that of comparable theories in JDM.

3.2 Open Questions and Future Directions

Taken together, while iCodes' level of universality for decision tasks is reduced compared to other theories in JDM, it is superior in its degree of precision due to its novel predictions for information search, its prediction for unique dependent variables, and the high degree of formalization of the model as a whole. Thus, iCodes has unique empirical content and, if corroborated by empirical testing, constitutes scientific advantage (Glöckner & Betsch, 2011). The manuscripts presented in this thesis supported iCodes' predictions to a great extent and, therefore, showed its merit as a starting point for the development of theories in JDM. In the following, I discuss remaining open questions and opportunities for further improvement of iCodes.

Extending iCodes

The analysis of iCodes' empirical content revealed, that, while iCodes' predictions are precise, there is room for improvement regarding their scope of application. One caveat that limits iCodes' applicability is the missing mechanism to predict stopping of search. That is, in tasks that require sequential search for information, iCodes currently cannot predict when information search should be stopped. Therefore, experiments investigating iCodes have often used only the first information search to test its predictions. Stopping of search, however, is an integral part of the decision process. Thus, as a first step for future theory development, a formalized stopping process has to be introduced into iCodes. One way to achieve this would be to introduce a desired level-of-confidence threshold into the information-search process (cf. Hausmann & Läge, 2008). As confidence judgments are derived from the difference in activations of option nodes, one possibility would be to add a threshold parameter for this activation difference: Once the difference is large enough to surpass the threshold, that is, once a certain level of confidence in the decision is achieved, information search is stopped and a decision is made. An alternative approach would be to assume that information search is stopped once the expected gain that can be derived from additional information for the final choice drops below a threshold (cf. Busemeyer & Rapoport, 1988; Kahan et al., 1967; Rapoport & Burkheimer, 1971). For this stopping mechanism, one could add a threshold parameter that is compared to the sum of activation of all concealed cue-value nodes and assume that, once this sum falls below a threshold, information search is stopped. Both implementations could account for variance in the amount of information searched by adjusting the threshold parameter. To choose one implementation as iCodes' stopping mechanism, extensive simulations are warranted to compare both mechanisms and potentially identify diagnostic conditions that permit an empirical test between them.

In addition to stopping of information search, several possible extensions of iCodes would increase its scope of applicability. To be able to account for additional criteria of information search such as discrimination rate (Newell et al., 2004) or cue-value salience (Platzer & Bröder, 2012), iCodes could, for example, be extended by an additional source node that also spreads activation to cues but proportional to differences of the aforementioned cue characteristics. Such extensions would increase the generalizability of iCodes, and the empirical tests would provide information about the underlying processes: For instance, Bröder, Scharf, Jekel, Glöckner, and Franke (2021) investigated the influence of salience on information search and the respective variant of iCodes. Their studies showed that while salience influenced information search, the observed search patterns did not qualitatively fit the proposed model extension that assumed that the cue-salience influence is comparable to the cue-validity influence on search. Rather, an implementation that connects an additional source node directly to the option nodes would be more adequate, such that activation of options that carry salient information is increased. Finally, iCodes' network structure could be extended to account for ordinal or continuous cue values, for example by introducing several links per cue value or adjusting the weights of the links. Being able to incorporate cue values that are not dichotomous would increase iCodes applicability further and, for example, allow the prediction of risky choices which often entail continuous cues.

Theories of Related Search Phenomena

While the prediction of attractiveness-influenced search is a unique feature of iCodes compared to other theories of multi-cue decision tasks, other theories in the domain of hypothesis testing (e.g., Doherty et al., 1979) or of motivated reasoning (e.g., P. Fischer et al., 2011) predict similar information-search behavior. Research on pseudodiagnosticity (also referred to as positive hypothesis testing, Klayman & Ha, 1987, 1989; Navarro & Perfors, 2011) investigates the integration of information concerning base rates and conjunctive probabilities when testing hypotheses. This research revealed that participants were more likely to request new information pertaining to the hypothesis under investigation instead of following Bayes' rule and requesting information about the alternative hypothesis. One explanation for this type of search behavior is that humans are not able to test two hypotheses at the same time and, therefore, focus on one hypothesis only (Mynatt et al., 1993). Research investigating motivated reasoning (often known as selective exposure, P. Fischer & Greitemeyer, 2010; P. Fischer et al., 2011; or confirmation bias, Klayman, 1995; for a review, see Nickerson, 1998) assumes that decision-makers are motivated to search for information that confirms their currently preferred option and, thus, bolsters their conviction about this option. Therefore, participants in studies investigating these phenomena are often already aware of the valence of information before they acquire it.

While the behavioral manifestations of both streams of research are similar to the search predictions of iCodes, there are substantial differences in the assumptions about the underlying processes and tasks to which the predictions are applied. Thus, a task for future research is to clarify the relationship of these phenomena with iCodes, that is, how motivational and cognitive processes interact and whether iCodes can provide a starting point for an integrative model. A first proposal to reconcile different streams of research on pre-decisional information distortions was put forward by Fraser-Mackenzie and Dror (2009) (for an alternative, see also P. Fischer et al., 2011). In their dual-process account they included both motivational aspects and an inherent striving for consistency. To benefit from the high degree of precision of iCodes, such a dual-process account could be implemented by extending iCodes to include motivational processes (cf. Shultz & Lepper, 1996).

Moderators and Process Measures

In addition to adapting and extending iCodes, future research should also test further boundary conditions of iCodes' predictions. It is reasonable to assume that the influence of option attractiveness on information search varies between individuals and situations. For example, research has shown that older adults differ in their decision-making behavior from younger adults (cf. Mata et al., 2015). Building on findings that these changes also affect information-search behavior (Mata & von Helversen, 2015) and older adults exhibit a preference for positive over negative stimuli (Reed & Carstensen, 2012), Scharf, Fischer, et al. (2021) tested and found support for the hypothesis that older adults show a stronger attraction search effect. A potential situational moderator of the influence of option attractiveness on search could be the framing of decisions, as it was shown that option-attractiveness influences are stronger in a gain compared to a loss frame (P. Fischer et al., 2008;

Sepulveda et al., 2020).

Besides identifying moderators of iCodes' predictions, it would be fruitful to test iCodes' predictions for additional dependent variables. A unique contribution of iCodes is that it predicts the time it takes decision-makers to choose which information to search for next. In a re-analysis of the experiments in Jekel et al. (2018) and in an additional, new experiment, Scharf, Jekel, et al. (2021) showed that iCodes could adequately predict information-search times and that the coherence of information as well as whether the decision task was set in a compensatory or non-compensatory environment were vital influences on the speed of information search. Next to predicting response times, one could investigate iCodes' assumed information-search process through mouse tracking (cf. Kieslich et al., 2019). Movements of the computer mouse have been shown to reflect cognitive conflict (Stillman et al., 2018) and could, thus, be used to directly assess whether the (in)coherence of information results in cognitive conflict during information search. In addition, the investigation of the temporal and spatial development of mouse trajectories would allow further tests of iCodes' predictions for the temporal development of the coherence influence on search. Going beyond behavioral process measures such as response times and mouse tracking, another avenue for future research of iCodes would be to investigate the neural underpinnings of coherence-based information search. For the class of EAMs, first steps have been made to map brain areas to decision processes in multi-attribute, multi-alternative choice (cf. Busemeyer et al., 2019). In future research, one could investigate neural correlates of the coherence influence on decision-making and search.

3.3 Conclusion

The recent developments in the reproducibility crisis have resulted in increasingly vocal calls for better theorizing in psychology (Glöckner et al., 2018; Smaldino, 2019), condensed in the slogan that "useful models produce better science" (Smaldino, 2019, p. 9). Jekel et al. (2018) introduced iCodes as a new, formalized theory of coherence-based decision-making and information search. The contribution of this thesis was to evaluate iCodes' theoretical properties, empirically test its predictions, and validate its underlying process assumptions. The three manuscripts presented in this thesis supported iCodes' predictions and underlined the importance of accounting for coherence-based influences in decision-making and search. With my thesis, I have provided a starting point for continued theorizing and hoped to have shown that iCodes is indeed a useful model in the field of JDM.

4 Bibliography

Bergert, F. B., & Nosofsky, R. M. (2007). A response-time approach to comparing generalized rational and take-the-best models of decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(1), 107–129. https://doi.org/10.1037/0278-7393.33.1.107

Bettman, J. R., & Kakkar, P. (1977). Effects of information presentation format on consumer information acquisition strategies. *Journal of Consumer Research*, *3*(4), 233–240. https://doi.org/10.1086/208672

Bredenkamp, J. (1980). *Theorie und Planung Psychologischer Experimente*. Steinkopff-Verlag.

Bröder, A. (2000). Assessing the empirical validity of the "take-the-best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1332–1346. https://doi.org/10.1037/0278-7393.26.5.1332

Bröder, A. (2003). Decision making with the "adaptive toolbox": Influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(4), 611–625. https://doi.org/10.1037/0278-7393.29.4.611

Bröder, A., & Newell, B. R. (2008). Challenging some common beliefs: Empirical work within the adaptive toolbox metaphor. *Judgment and Decision Making*, *3*(3), 205–214.

Bröder, A., Scharf, S. E., Jekel, M., Glöckner, A., & Franke, N. (2021). *Salience effects in information acquisition: No evidence for a top-down coherence influence* (Manuscript submitted for publication).

Bröder, A., & Schiffer, S. (2006). Adaptive flexibility and maladaptive routines in selecting fast and frugal decision strategies. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*(4), 904–918. https://doi.org/10.1037/0278-7393.32.4.904

Brownstein, A. L. (2003). Biased predecision processing. *Psychological Bulletin*, *129*(4), 545–568. https://doi.org/10.1037/0033-2909.129.4.545

Busemeyer, J. R., & Diederich, A. (2002). Survey of decision field theory. *Mathematical Social Sciences*, *43*(3), 345–370. https://doi.org/10.1016/S0165-4896(02)00016-1

Busemeyer, J. R., Gluth, S., Rieskamp, J., & Turner, B. M. (2019). Cognitive and neural bases of multi-attribute, multi-alternative, value-based decisions. *Trends in Cognitive Sciences*, *23*(3), 251–263. https://doi.org/10.1016/j.tics.2018.12.003

Busemeyer, J. R., & Johnson, J. G. (2004). Computational models of decision making. In D. J. Koehler & N. Harvey (Eds.), *Blackwell handbook of judgment and decision making* (pp. 133–154). Blackwell Publishing Ltd. https://doi.org/10.1002/9780470752937.ch7

Busemeyer, J. R., & Rapoport, A. (1988). Psychological models of deferred decision making. *Journal of Mathematical Psychology*, *32*(2), 91–134. https://doi.org/10.1016/0022-2496(88)90042-9

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459. https://doi.org/10.1037/0033-295X.100.3.432

DeKay, M. L. (2015). Predecisional information distortion and the self-fulfilling prophecy of early preferences in choice. *Current Directions in Psychological Science*, *24*(5), 405–411. https://doi.org/10.1177/0963721415587876

DeKay, M. L., Miller, S. A., Schley, D. R., & Erford, B. M. (2014). Proleader and antitrailer information distortion and their effects on choice and postchoice memory. *Organizational Behavior and Human Decision Processes*, *125*(2), 134–150. https://doi.org/10.1016/j.obhdp.2014.07.003

DeKay, M. L., Stone, E. R., & Miller, S. A. (2011). Leader-driven distortion of probability and payoff information affects choices between risky prospects. *Journal of Behavioral Decision Making*, *24*(4), 394–411. https://doi.org/https://doi.org/10.1002/bdm.699

Dieckmann, A., & Rieskamp, J. (2007). The influence of information redundancy on probabilistic inferences. *Memory & Cognition*, *35*(7), 1801–1813. https://doi.org/10.3758/BF03193511

Doherty, M. E., Mynatt, C. R., Tweney, R. D., & Schiavo, M. D. (1979). Pseudodiagnosticity. *Acta Psychologica*, *43*(2), 111–121. https://doi.org/10.1016/0001-6918(79)90017-9

Edwards, W. (1954). The theory of decision making. *Psychological Bulletin*, *51*(4), 380–417. https://doi.org/10.1037/h0053870

Erev, I., & Barron, G. (2005). On adaptation, maximization, and reinforcement learning among cognitive strategies. *Psychological Review*, *112*(4), 912–931. https://doi.org/10.1037/0033-295X.112.4.912

Ettlin, F., Bröder, A., & Henninger, M. (2015). A new task format for investigating information search and organization in multiattribute decisions. *Behavior Research Methods*, *47*(2), 506–518. https://doi.org/10.3758/s13428-014-0482-y

Ferguson, C. J., & Heene, M. (2012). A vast graveyard of undead theories: Publication bias and psychological science's aversion to the null. *Perspectives on Psychological Science*, *7*(6), 555–561. https://doi.org/10.1177/1745691612459059

Ferguson, T. S. (1989). Who solved the secretary problem? *Statistical Science*, *4*(3), 282–289. https://doi.org/10.1214/ss/1177012493

Fischer, P., & Greitemeyer, T. (2010). A new look at selective-exposure effects: An integrative model. *Current Directions in Psychological Science*, *19*(6), 384–389. https://doi.org/10.1177/0963721410391246

Fischer, P., Lea, S., Kastenmüller, A., Greitemeyer, T., Fischer, J., & Frey, D. (2011). The process of selective exposure: Why confirmatory information search weakens over time. *Organizational Behavior and Human Decision Processes*, *114*(1), 37–48. https://doi.org/10.1016/j.obhdp.2010.09.001

Fischer, P., Schulz-Hardt, S., & Frey, D. (2008). Selective exposure and information quantity: How different information quantities moderate decision makers' preference for consistent and inconsistent information. *Journal of Personality and Social Psychology*, *94*(2), 231–244. https://doi.org/10.1037/0022-3514.94.2.94.2.231

Fisher, G. (2017). An attentional drift diffusion model over binary-attribute choice. *Cognition*, *168*, 34–45. https://doi.org/10.1016/j.cognition.2017.06.007

Fraser-Mackenzie, P. A. F., & Dror, I. E. (2009). Selective information sampling: Cognitive coherence in evaluation of a novel item. *Judgment and Decision Making*, *4*(4), 307–316.

Gigerenzer, G. (2001). The adaptive toolbox. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 37 –50). MIT Press.

Gigerenzer, G., Dieckmann, A., & Gaissmaier, W. (2014). Efficient cognition through limited search. In P. M. Todd, G. Gigerenzer, & The ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 241–273). Oxford University Press.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*(1), 451–482. https://doi.org/10.1146/annurev-psych-120709-145346

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669. https://doi.org/10.1037/0033-295X.103.4.650

Gigerenzer, G., & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. *Simple heuristics that make us smart* (pp. 3–34). Oxford University Press.

Glöckner, A. (2008). Does intuition beat fast and frugal heuristics? A systematic empirical analysis. In H. Plessner, C. Betsch, & T. Betsch (Eds.), *Intuition in judgment and decision making* (pp. 309–325). Lawrence Erlbaum Associates Publishers.

Glöckner, A. (2009). Investigating intuitive and deliberate processes statistically: The multiple-measure maximum likelihood strategy classification method. *Judgment and Decision Making*, *4*(3), 186–199.

Glöckner, A., & Betsch, T. (2008a). Modeling option and strategy choices with connectionist networks: Towards an integrative model of automatic and deliberate decision making. *Judgment and Decision Making*, *3*(3), 215–228.

Glöckner, A., & Betsch, T. (2008b). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(5), 1055–1075. https://doi.org/10.1037/0278-7393.34.5.1055

Glöckner, A., & Betsch, T. (2011). The empirical content of theories in judgment and decision making: Shortcomings and remedies. *Judgment and Decision Making*, *6*(8), 711–721.

Glöckner, A., & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologica*, *139*(3), 532–542. https://doi.org/10.1016/j.actpsy.2012.01.009

Glöckner, A., Betsch, T., & Schindler, N. (2010). Coherence shifts in probabilistic inference tasks. *Journal of Behavioral Decision Making*, *23*(5), 439–462. https://doi.org/10.1002/bdm.668

Glöckner, A., Fiedler, S., & Renkewitz, F. (2018). Belastbare und effiziente Wissenschaft. *Psychologische Rundschau*, *69*(1), 22–36. https://doi.org/10.1026/0033-3042/a000384

Glöckner, A., Heinen, T., Johnson, J. G., & Raab, M. (2012). Network approaches for expert decisions in sports. *Human Movement Science*, *31*(2), 318–333. https://doi.org/10.1016/j.humov.2010.11.002

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666. https://doi.org/10.1016/j.cognition.2014.08.017

Goldstein, W. M., & Hogarth, R. M. (1997). Judgment and decision research: Some historical context. *Research on judgment and decision making: Currents, connections, and controversies* (pp. 3–65). Cambridge University Press.

Hastie, R. (2001). Problems for judgment and decision making. *Annual Review of Psychology*, *52*(1), 653–683. https://doi.org/10.1146/annurev.psych.52.1.653

Hastie, R., & Dawes, R. M. (2010). Thinking and deciding. *Rational choice in an uncertain world: The psychology of judgment and decision making* (2nd ed., pp. 1–22). SAGE Publications.

Hau, R., Pleskac, T. J., Kiefer, J., & Hertwig, R. (2008). The description–experience gap in risky choice: The role of sample size and experienced probabilities. *Journal of Behavioral Decision Making*, *21*(5), 493–518. https://doi.org/https://doi.org/10.1002/bdm.598

Hausmann, D., & Läge, D. (2008). Sequential evidence accumulation in decision making: The individual desired level of confidence can explain the extent of information acquisition. *Judgment and Decision Making*, *3*(3), 229–243.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x

Hilbig, B. E., & Moshagen, M. (2014). Generalized outcome-based strategy classification: Comparing deterministic and probabilistic choice models. *Psychonomic Bulletin & Review*, *21*(6), 1431–1443. https://doi.org/10.3758/s13423-014-0643-0

Holyoak, K. J., & Simon, D. (1999). Bidirectional reasoning in decision making by constraint satisfaction. *Journal of Experimental Psychology: General*, *128*(1), 3–31. https://doi.org/10.1037/0096-3445.128.1.3

Jekel, M., Glöckner, A., & Bröder, A. (2018). A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect. *Psychological Review*, *125*(5), 744–768. https://doi.org/10.1037/rev0000107

Kahan, J. P., Rapoport, A., & Jones, L. V. (1967). Decision making in a sequential search task. *Perception & Psychophysics*, *2*(8), 374–376. https://doi.org/10.3758/BF03210074

Kieslich, P. J., Henninger, F., Wulff, D. U., Haslbeck, J. M., & Schulte-Mecklenbeck, M. (2019). Mouse-tracking: A practical guide to implementation and analysis. In M. Schulte-Mecklenbeck, A. Kühberger, & J. G. Johnson (Eds.), *A handbook of process tracing methods* (2nd ed., pp. 111–130). Routledge.

Klayman, J. (1995). Varieties of confirmation bias (J. Busemeyer, R. Hastie, & D. L. Medin, Eds.). *Psychology of Learning and Motivation*, *32*, 385–418. https://doi.org/10.1016/S0079-7421(08)60315-1

Klayman, J., & Ha, Y.-W. (1987). Confirmation, disconfirmation, and information in hypothesis testing. *Psychological Review*, *94*(2), 211–228. https://doi.org/10.1037/0033-295X.94.2.211

Klayman, J., & Ha, Y.-W. (1989). Hypothesis testing in rule dscovery: Strategy, structure, and content. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *15*(4), 596–604.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krajbich, I., Lu, D., Camerer, C., & Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00193

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review*, *11*(2), 343–352. https://doi.org/10.3758/BF03196581

Leuker, C., Pachur, T., Hertwig, R., & Pleskac, T. J. (2019). Do people exploit risk–reward structures to simplify information processing in risky choice?

Journal of the Economic Science Association, *5*(1), 76–94. https://doi.org/10.1007/s40881-019-00068-y

Lieder, F., & Griffiths, T. L. (2017). Strategy selection as rational metareasoning. *Psychological Review*, *124*(6), 762–794. https://doi.org/10.1037/rev0000075

Marewski, J. N. (2010). On the theoretical precision and strategy selection problem of a single-strategy approach: A comment on Glöckner, Betsch, and Schindler (2010). *Journal of Behavioral Decision Making*, *23*(5), 463–467. https://doi.org/10.1002/bdm.680

Marewski, J. N., Bröder, A., & Glöckner, A. (2018). Some metatheoretical reflections on adaptive decision making and the strategy selection problem. *Journal of Behavioral Decision Making*, *31*(2), 181–198. https://doi.org/https://doi.org/10.1002/bdm.2075

Mata, R., Josef, A. K., & Lemaire, P. (2015). Adaptive decision making and aging. In T. M. Hess, J. Strough, & C. E. Löckenhoff (Eds.), *Aging and Decision Making. Empirical and Applied Perspectives* (pp. 105–126). Elsevier.

Mata, R., & von Helversen, B. (2015). Search and the aging mind: The promise and limits of the cognitive control hypothesis of age differences in search. *Topics in Cognitive Science*, *7*(3), 416–427. https://doi.org/10.1111/tops.12139

Montgomery, H. (1989). From cognition to action : The search for dominance in decision making. In H. Montgomery & Svenson, O. (Eds.), *Process and structure in human decision making* (pp. 23–49). Wiley.

Mynatt, C. R., Doherty, M. E., & Dragan, W. (1993). Information relevance, working memory, and the consideration of alternatives. *The Quarterly Journal of Experimental Psychology Section A*, *46*(4), 759–778. https://doi.org/10.1080/14640749308401038

Navarro, D., & Perfors, A. (2011). Hypothesis generation, sparse categories, and the positive test strategy. *Psychological Review*, *118*(1), 120–134. https://doi.org/10.1037/a0021110

Newell, B. R. (2005). Re-visions of rationality? *Trends in Cognitive Sciences*, *9*(1), 11–15. https://doi.org/10.1016/j.tics.2004.11.005

Newell, B. R., & Lee, M. D. (2011). The right tool for the job? Comparing an evidence accumulation and a naive strategy selection model of decision making. *Journal of Behavioral Decision Making*, *24*(5), 456–481. https://doi.org/10.1002/bdm.703

Newell, B. R., Rakow, T., Weston, N. J., & Shanks, D. R. (2004). Search strategies in decision making: The success of "success". *Journal of Behavioral Decision Making*, *17*(2), 117–137. https://doi.org/10.1002/bdm.465

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, *2*(2), 175–220. https://doi.org/10.1037/1089-2680.2.2.175

Noguchi, T., & Stewart, N. (2018). Multialternative decision by sampling: A model of decision making constrained by process data. *Psychological Review*, *125*(4), 512–544. https://doi.org/10.1037/rev0000102

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251). https://doi.org/10.1126/science.aac4716

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*(1), 190–206. https://doi.org/10.1016/j.actpsy.2013.06.003

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. https://doi.org/10.1037/0278-7393.14.3.534

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. University Press.

Pitz, G. F., Reinhold, H., & Scott, E. (1969). Strategies of information seeking in deferred decision making. *Organizational Behavior & Human Performance*, *4*(1), 1–19. https://doi.org/10.1016/0030-5073(69)90028-2

Platzer, C., & Bröder, A. (2012). Most people do not ignore salient invalid cues in memory-based decisions. *Psychonomic Bulletin & Review*, *19*(4), 654–661. https://doi.org/10.3758/s13423-012-0248-4

Popper, K. (1935). *Logik der Forschung*. Springer-Verlag.

Rapoport, A., & Burkheimer, G. J. (1971). Models for deferred decision making. *Journal of Mathematical Psychology*, *8*(4), 508–538. https://doi.org/10.1016/0022-2496(71)90005-8

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007

Read, S. J., Vanman, E. J., & Miller, L. C. (1997). Connectionism, parallel constraint satisfaction processes, and gestalt principles: (Re)Introducing cognitive dynamics to social psychology. *Personality and Social Psychology Review*, *1*(1), 26–53. https://doi.org/10.1207/s15327957pspr0101_3

Reed, A. E., & Carstensen, L. L. (2012). The theory behind the age-related positivity effect. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00339

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. https://doi.org/10.1016/j.actpsy.2007.05.004

Rieskamp, J., & Otto, P. E. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General*, *135*(2), 207–236. https://doi.org/10.1037/0096-3445.135.2.207

Rumelhart, D. E., & McClelland, J. L. (Eds.). (1986). *Parallel distributed processing: Explorations in the microstructure of cognition: Vol. 1. Foundations.* MIT Press Bradford.

Russo, J. E., Carlson, K. A., Meloy, M. G., & Yong, K. (2008). The goal of consistency as a cause of information distortion. *Journal of Experimental Psychology: General*, *137*(3), 456–470. https://doi.org/10.1037/a0012786

Saad, G., & Russo, J. E. (1996). Stopping criteria in sequential choice. *Organizational Behavior and Human Decision Processes*, *67*(3), 258–270. https://doi.org/10.1006/obhd.1996.0078

Scharf, S. E., Fischer, M., & Schnuerch, M. (2021). *The attraction search effect in younger and older adults* (Manuscript in preparation).

Scharf, S. E., Jekel, M., & Bröder, A. (2021). *Model-based prediction of information search times in multi-attribute decisions* (Manuscript in preparation).

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488–512.

Scheibehenne, B., Rieskamp, J., & Wagenmakers, E.-J. (2013). Testing adaptive toolbox models: A Bayesian hierarchical approach. *Psychological Review*, *120*(1), 39–64. https://doi.org/10.1037/a0030777

Seale, D. A., & Rapoport, A. (1997). Sequential decision making with relative ranks: An experimental investigation of the "Secretary Problem". *Organizational Behavior and Human Decision Processes*, *69*(3), 221–236. https://doi.org/10.1006/obhd.1997.2683

Sepulveda, P., Usher, M., Davies, N., Benson, A., Ortoleva, P., & Martino, B. D. (2020). Visual attention modulates the integration of goal-relevant evidence and not value. *bioRxiv*, 2020.04.14.031971. https://doi.org/10.1101/2020.04.14.031971

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, *6*(12), 1317–1322. https://doi.org/10.1038/nn1150

Shultz, T. R., & Lepper, M. R. (1996). Cognitive dissonance reduction as constraint satisfaction. *Psychological Review*, *103*(2), 219–240. https://doi.org/10.1037/0033-295X.103.2.219

Simon, D., Krawczyk, D. C., Bleicher, A., & Holyoak, K. J. (2008). The transience of constructed preferences. *Journal of Behavioral Decision Making*, *21*(1), 1–14. https://doi.org/https://doi.org/10.1002/bdm.575

Simon, D., Krawczyk, D. C., & Holyoak, K. J. (2004). Construction of preferences by constraint satisfaction. *Psychological Science*, *15*(5), 331–336. https://doi.org/10.1111/j.0956-7976.2004.00678.x

Simon, H. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics*, *69*(1), 99–118. https://doi.org/10.2307/1884852

Simon, H. (1957). *Models of man; social and rational*. Wiley.

Smaldino, P. (2019). Better methods can't make up for mediocre theory. *Nature*, *575*(7781), 9. https://doi.org/10.1038/d41586-019-03350-5

Söllner, A., Bröder, A., & Hilbig, B. E. (2013). Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making? *Judgment and Decision Making*, *8*(3), 278–298.

Stillman, P. E., Shen, X., & Ferguson, M. J. (2018). How mouse-tracking can advance social cognitive theory. *Trends in Cognitive Sciences*, *22*(6), 531–543. https://doi.org/10.1016/j.tics.2018.03.012

Todd, P. M., & Gigerenzer, G. (2003). Bounding rationality to the world. *Journal of Economic Psychology*, *24*(2), 143–165. https://doi.org/10.1016/S0167-4870(02)00200-3

Trueblood, J. S., Brown, S. D., & Heathcote, A. (2014). The multiattribute linear ballistic accumulator model of context effects in multialternative choice. *Psychological Review*, *121*(2), 179–205. https://doi.org/10.1037/a0036137

A Acknowledgements

Silent gratitude isn't much use to anyone.

by Gertrude Stein

After almost 4.5 years, I can finally thank the people without whom I would never have made it to where I am today. Many have accompanied me on my PhD journey, and I am grateful for every shared moment of joy, every word of encouragement, and every memory that I share with each and every one of them.

First and foremost, I want to thank Arndt Bröder for paving my way into academia and encouraging me to pursue my interest in network models. He always supported me, be it with critical, yet enlightening questions, inspiring discussions over coffee, or last-minute feedback. I am grateful to Andreas Glöckner for teaching me the importance of theoretical precision, providing me with the opportunity to work in different, scientific environments, and shaping the way I conduct research today. I want to thank Marc Jekel, who laid the foundations for this thesis by teaching me R and computational modeling. I will be forever grateful for his unending patience and invaluable suggestions for every network-related question I ever had. My thanks also go to Edgar Erdfelder and Daniel Heck, who always offered new insights and helpful advice in countless CDSS colloquia and anytime I needed it.

Many colleagues that have become friends helped me on my academic journey. I am deeply grateful to Dorothee Mischkowski, who taught me so much about academia (and life in general) and who always had a sympathetic ear for any major or minor crisis along the way. I am indebted to Pascal Kieslich, who was always there for me from day one, always ready to discuss anything and everything, and without whom I would not be where I am today. I also want to thank Felix Henninger, whose kind words of encouragement and keen understanding of formalized models in JDM more than once saved my day.

I was lucky that I started my PhD with some of the most brilliant and kind people the universe has to offer. I want to thank Lili, for being there for all my academic firsts, for always having my back and being by my side, and for reminding me to enjoy my life to the fullest, whenever I needed it; Mirka, for inspiring me to think outside of the box, for sharing her wisdom, and for supporting me in every way imaginable; Stella and Sebastian, for being my moral support when times were tough, for being my partners in crime in completing this thesis, and for always being up for any tomfoolery; Jana, who was always there for me and whose never-ending encouragement kept me motivated in the last few weeks; and David and Franzi, for being the best floor mates one could wish for and supporting me with their insights and advice.

I would like to thank my colleagues in Mannheim, in particular Sofia, Tong, Susanne, and Caroline, who supported me along the way; our student assistants, who helped me in every step of the research process; my friends and colleagues from the doctoral convents, Arne, Julia, Kilian, Philip, Therry, who showed me the benefits of building connections with PhD students outside of psychology; Konstantin, who started this journey with me and introduced me into the world of university politics; and everyone in the CDSS, for their intellectual and organizational support.

Special thanks are due to my friends that have already been there for me before I started my PhD. I want to thank Elena, Feli, Kathi K., Marisa, Patty, Steffen, for being the best group of friends one could wish for. I want to thank Malte, for going with me through the ups and downs during a PhD, and especially Martin, for being my co-author as well as being like family to me. I want to thank Lisa and Simone, for giving their best to improve my creativity; Kathi H., for being so much more than just my running partner over the past few years; and Tim, for always offering a reality check when I needed one.

Finally, I cannot begin to express my thanks to my parents, Hanns-Peter and Martha, and my brothers, Gregor and Veit, and their families, who supported me unconditionally on every step of the way. Last but not least, I am forever grateful to Stefan for being my best friend, my rock, and my guiding light. You always believed in me. Thank you.

Sophie E. Scharf
Mannheim, January 2021

B Statement of Originality

1. I hereby declare that the presented doctoral dissertation with the title *Testing and Validating a Coherence-Based Model for Decision-Making and Search* is my own work.
2. I did not seek unauthorized assistance of a third party and I have employed no other sources or means except the ones listed. I clearly marked any quotations derived from the works of others.
3. I did not present this doctoral dissertation or parts of it at any other higher education institution in Germany or abroad.
4. I hereby conform the accuracy of the declaration above.
5. I am aware of the significance of this declaration and the legal consequences in case of untrue or incomplete statements.

I affirm in lieu of oath that the statements above are to the best of my knowledge true and complete.

Signature:

Date: 01.02.2021

C Co-Authors' Statements

Co-Author: Arndt Bröder

I hereby confirm that the following manuscripts included in the thesis *Testing and Validating a Coherence-Based Model for Decision-Making and Search* were primarily conceived and written by Sophie E. Scharf, PhD candidate at the *Center for Doctoral Studies in Social and Behavioral Sciences* of the *Graduate School of Economic and Social Sciences* at the University of Mannheim:

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488-512.

Scharf, S. E., Bröder, A., Jekel, M., & Glöckner, A. (2021). *Coherence influences on attention allocation and visual information search in decisions with open information displays.* Manuscript submitted for publication.

I sign this statement to the effect that Sophie E. Scharf is credited as the primary source of the ideas and the main author of the above-mentioned articles. She designed and collected data for two out of three experiments in Scharf et al. (2019) and all experiments in Scharf et al. (2021). She performed the analyses, wrote the first drafts, and contributed to improving and revising both manuscripts. I contributed to designing the first experiment in Scharf et al. (2019) and aided in the conceptualizations of the remaining experiments in both manuscripts. Further, I contributed to developing the research questions and to structuring the theoretical background and discussions of the manuscripts, suggested ideas for the analyses and their interpretations, and provided recommendations for making the message of the articles clearer.

Prof. Dr. Arndt Bröder
Mannheim, January 2021

Co-Author: Andreas Glöckner

I hereby confirm that the following manuscripts included in the thesis *Testing and Validating a Coherence-Based Model for Decision-Making and Search* were primarily conceived and written by Sophie E. Scharf, PhD candidate at the *Center for Doctoral Studies in Social and Behavioral Sciences* of the *Graduate School of Economic and Social Sciences* at the University of Mannheim:

Scharf, S. E., Jekel, M., & Glöckner, A. (2021). *Testing an extension of the iCodes model to account for situation, person, and task specific variation in the attraction search effect.* Manuscript submitted for publication.

Scharf, S. E., Bröder, A., Jekel, M., & Glöckner, A. (2021). *Coherence influences on attention allocation and visual information search in decisions with open information displays.* Manuscript submitted for publication.

I sign this statement to the effect that Sophie E. Scharf is credited as the primary source of the ideas and the main author of the above-mentioned articles. She designed and conducted the experiments, performed the analyses, wrote the first drafts, and was responsible for revising both manuscripts. I contributed to developing and refining the research questions in both manuscripts and provided support in designing the experiments and implementing the eye tracking methodology. Further, I contributed to refining and structuring the theoretical background and discussions of the manuscripts, suggested ideas for the analyses and their interpretations, and provided recommendations for making the message of the articles clearer.

Prof. Dr. Andreas Glöckner
Köln, January 2021

Co-Author: Marc Jekel

I hereby confirm that the following manuscripts included in the thesis *Testing and Validating a Coherence-Based Model for Decision-Making and Search* were primarily conceived and written by Sophie E. Scharf, PhD candidate at the *Center for Doctoral Studies in Social and Behavioral Sciences* of the *Graduate School of Economic and Social Sciences* at the University of Mannheim:

Scharf, S. E., Jekel, M., & Glöckner, A. (2021). *Testing an extension of the iCodes model to account for situation, person, and task specific variation in the attraction search effect.* Manuscript submitted for publication.

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Dr. Marc Jekel
Köln, January 2021

Co-Author: Monika Wiegelmann

I hereby confirm that the following manuscript included in the thesis *Testing and Validating a Coherence-Based Model for Decision-Making and Search* was primarily conceived and written by Sophie E. Scharf, PhD candidate at the *Center for Doctoral Studies in Social and Behavioral Sciences* of the *Graduate School of Economic and Social Sciences* at the University of Mannheim:

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488-512.

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Monika Wiegelmann
Mannheim, January 2021

D Copies of Articles

Judgment and Decision Making, Vol. 14, No. 4, July, 2019, pp. 488–512

Information search in everyday decisions: The generalizability of the attraction search effect

Sophie E. Scharf*† Monika Wiegelmann‡ Arndt Bröder‡

Abstract

The recently proposed *integrated coherence-based decisions and search model* (iCodes) makes predictions for search behavior in multi-attribute decision tasks beyond those of classic decision-making heuristics. More precisely, it predicts the *Attraction Search Effect* that describes a tendency to search for information for the option that is already attractive given the available evidence. To date, the Attraction Search Effect has been successfully tested using a hypothetical stock-market game that was highly stylized and specifically designed to be highly diagnostic. In three experiments, we tested whether the Attraction Search Effect generalizes to different semantic contexts, different cue-value patterns, and a different presentation format than the classic matrix format. Across all experiments, we find evidence for information-search behavior that matches iCodes's information-search prediction. Therefore, our results corroborate not only the generalizability of the Attraction Search Effect in various contexts but also the inherent process assumptions of iCodes.

Keywords: attraction search effect, information search, generalizability

1 Introduction

When faced with a decision, we often have to search for information that enables us to weigh the advantages and disadvantages of each option against each other. Information search is especially important, if the decision at hand has non-trivial consequences, such as when buying a car, deciding on a job offer, or taking out insurance. Despite the importance of information search for decision making, psychological decision-making models have usually focused more on the processes of integrating information rather than the processes behind searching for information (Gigerenzer et al., 2014).

Aware of this lack of specified information-search process models, Jekel et al. (2018) recently extended the parallel constraint satisfaction model for decision making (PCS-DM; Glöckner et al., 2014) to include information search in multi-attribute decision tasks. The new integrated coherence-based decision and search model (iCodes) makes detailed predictions for the information-search process in multi-attribute decisions (Jekel et al., 2018). One core prediction of iCodes is the *Attraction Search Effect*, which states that people tend to search for information about the option that is currently supported by the already available evidence. The Attraction Search Effect and iCodes itself have received initial support from three experiments and the reanalyses of five already published experiments (Jekel et al., 2018).

The original experiments by Jekel et al. (2018) used a probabilistic-inference task presented as a hypothetical stock-market game with cue-value patterns that were specifically designed to be highly diagnostic for the Attraction Search Effect. In our view, it is essential to demonstrate that the support for the Attraction Search Effect found by Jekel et al. (2018) was not due to arbitrary design choices in their studies. The goal of the present work is to test the generalizability of the Attraction Search Effect to different settings. With data from three online experiments, we test whether the Attraction Search Effect replicates in different, more diverse semantic context settings. As a next step, we investigate whether the Attraction Search Effect can be found with randomized cue-value patterns as well. Finally, we evaluate whether the Attraction Search Effect also emerges when information is not presented in a classic mouselab-type setting (first introduced by Johnson et al., 1989, referred to as mouselab in the following) but in a more realistic, simulated online shop. Since iCodes is a new model, demonstrating that its core prediction generalizes to different settings strengthens the relevance and reach of the model.

In the following paragraphs, we will first take a closer look at iCodes's prediction of information search in general and

This work was supported by the University of Mannheim's Graduate School of Economic and Social Sciences funded by the German Research Foundation (DFG). The authors thank Laura Büche, Daniela Kauschke, and Luca Pier for their support in creating stimulus materials for Experiment 3, Yury Shevchenko for his support in programming Experiment 2, two anonymous reviewers for their helpful comments in the revision process, and Marc Jekel for helpful comments on earlier versions of this manuscript.

*School of Social Sciences, University of Mannheim, L13, 17, 68161 Mannheim, Germany. Email: sophie.scharf@gess.uni-mannheim.de.

†Social Cognition Center Cologne, University of Cologne, Germany

‡School of Social Sciences, University of Mannheim, Germany.

the Attraction Search Effect specifically. After presenting already existing evidence for iCodes's core prediction, we will argue why generalizability is an important issue and present data from three experiments that test exactly this generalizability of the Attraction Search Effect. In these three studies, we gradually move away from the original study setup by (a) demonstrating the Attraction Search Effect in other semantic domains, (b) extending the range of domains and relaxing the cue-value patterns, and (c) moving away from the matrix format in a simulated online-shop setting.

2 The integrated, coherence-based decision and search model

The original PCS-DM is a network model that successfully predicts choices, decision times, and decision confidence for multi-attribute decisions in different contexts (Glöckner et al., 2012, 2014; Glöckner & Betsch, 2012; Glöckner & Hodges, 2010; Glöckner et al., 2010). However, one shortcoming of PCS-DM is that it models information integration only and is thus applicable only to decision situations that do not require information search (Marewski, 2010). Therefore, Jekel et al. (2018) have recently extended PCS-DM to include information-search processes. This new model shares in principle the same basic network structure and the same assumptions regarding the underlying decision process with its predecessor PCS-DM. The crucial extension is an additional layer of nodes that is included in the network structure. This layer represents the cue values present in the decision situation. In the following paragraphs, we will introduce how iCodes specifies the information-search process and how it predicts the Attraction Search Effect. For the exact model specification and formalization, please refer to Jekel et al. (2018).

2.1 The prediction of information search in iCodes

In a multi-attribute decision task, the decision maker is presented with at least two options for which information is provided in the form of attributes or cues (Harte & Koele, 2001). Depending on the specific task, the goal of the decision maker is to either choose the option that maximizes an objective criterion value (Glöckner et al., 2010), such as buying the most successful stock, or to choose the option that maximizes a subjective criterion value (Payne et al., 1993), such as buying the preferred sweater. The cues provide information about the options in form of cue values that can be positive evaluations of the respective option, often represented by a "+", or negative evaluations, often represented by a "−". In probabilistic-inference tasks, the cues usually differ in their validity, that is, they differ in how often they correctly evaluate an option as better than the other option(s) on the objective criterion (Gigerenzer & Goldstein, 1996). Besides positive and negative evaluations, cue values can also be hidden and have to be searched for, which is represented by a "?". An example trial of such a multi-attribute decision task with two options and two cues is shown in Figure 1.

The information in such a multi-attribute decision task is represented in iCodes as a network (Jekel et al., 2018). There are nodes for the options, cues, and cue values that are connected via links as depicted in Figure 1. The information-search process of iCodes is modeled as a spread of activation through this network that is initiated by the source node at the bottom of the network. Activation is spread between nodes via the connecting links. The spread of activation continues until the activation of each node has stabilized and, therefore, does not change substantially anymore. At this point, the network as a whole is stable and the model predicts that the concealed cue value whose node received the most activation during this process is opened next. The activation, that concealed cue-value nodes receive, stems from two sources in the network (Jekel et al., 2018). These sources are the option and cue nodes that are connected to searchable cue values via unidirectional links. Thus, nodes of concealed cue values receive activation only but do not continue the spread of activation further. These links are unidirectional to represent that concealed cue values do not carry any information with regard to the options or cues. Note that once a concealed cue value is opened the unidirectional links become bidirectional indicating that the information of this cue value is now available. The amount of activation that nodes of searchable cue values receive from cue nodes is proportional to their respective validities. Thus, the higher the validity of a cue, the more activation the corresponding cue-value nodes receive. The activation received from the option nodes depends on the current evidence for the options. Thus, the more the current evidence favors one option over another, the more activation the corresponding cue-value nodes receive - via the links between cue-value nodes and options. Both sources of activation are assumed to influence search in an additive manner. Therefore, both the respective cue's validity and the respective option's evidence determine iCodes's search prediction for a concealed cue value.

2.1.1 The Attraction Search Effect

Formal models that predict information search in multi-attribute decision tasks often assume that information is searched for cue-wise or option-wise and most often following the order of cues' validities (Payne et al., 1988; Lee & Cummins, 2004; Gigerenzer & Goldstein, 1996). These search directions are assumed to be independent of the already available evidence. In the example trial in Figure 1, in which one cue value is already available, these models would therefore predict that the valence of this cue

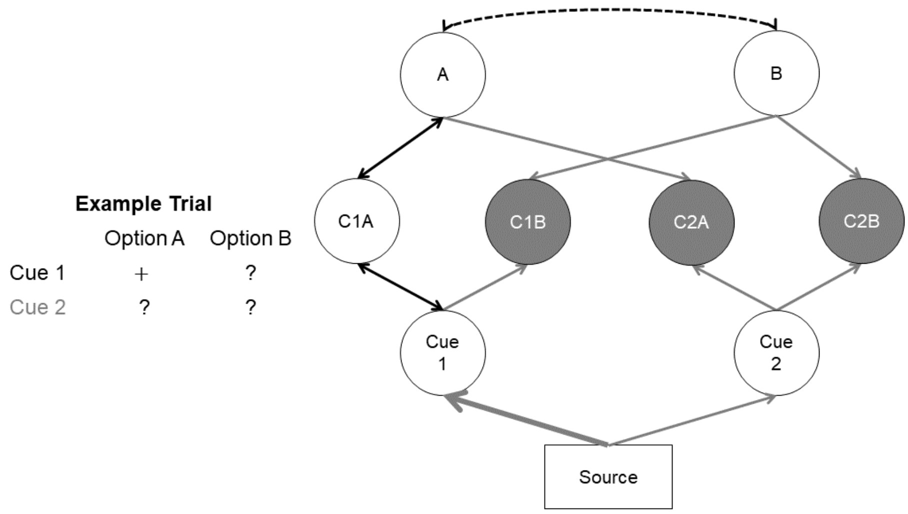

Figure 1: The translation of a probabilistic-inference task into the network structure of iCodes. In this example task, the first cue, which is more valid than the second cue, makes a positive statement regarding Option A and all other information is still hidden. The options are represented by the option nodes in the top layer of the network and are connected by an inhibitory, bidirectional link (dashed line). The cue values are included in the next layer of nodes where the white node represents the already available information and the gray nodes represent still concealed information. Below the layer of cue-value nodes is the layer of cue nodes. The source node on the bottom of the network initializes the spread of activation. The activation the cue nodes receive is proportional to their respective validities, as indicated here by the thickness of the link. The black arrows in the network represent bidirectional links, whereas gray arrows represent unidirectional links. Adapted from "A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect," by M. Jekel, A. Glöckner, and A. Bröder, 2018, *Psychological Review, 125*, p. 746. Copyright 2018 by the American Psychological Association.

value would not matter for whether information is searched cue-wise or option-wise. ICodes, however, predicts that the already available evidence influences information search (Jekel et al., 2018). This is due to the fact that iCodes assumes a joint influence of the cues' validities and the options' current attractiveness on information search. The influence of the cues' validities leads to iCodes's prediction that, all things being equal, cue values from highly valid cues are more likely to be searched for than cue values from less valid cues. The influence of the current evidence on information search in the formalized iCodes model also leads to an additional qualitative search prediction: Cue values with information on the currently preferred option are more likely to be searched for than cue values with information on the less attractive option. This prediction has been coined as the Attraction Search Effect by Jekel et al. (2018).

Searching information on the currently attractive option has also been shown in information-search paradigms outside the realm of probabilistic-inference tasks. One common observation is information-search behavior consistent with selective exposure (Frey, 1986; Hart et al., 2009; Fischer & Greitemeyer, 2010). Selective exposure is the tendency to search for information that supports the currently preferred option. In the literature, this pattern of information search is often considered to mainly stem from the motivation to defend one's prior beliefs or prior position (Hart et al., 2009; Fischer & Greitemeyer, 2010).[1] In the standard paradigm of selective exposure subjects, therefore, know the valence of the searchable information a priori (Fischer et al., 2011). This a priori knowledge constitutes the key difference of selective exposure and the Attraction Search Effect. The Attraction Search Effect cannot be driven merely by the motivation to defend one's preferred option since this would require knowing beforehand whether the concealed information supports or contradicts the currently attractive option. Rather, the mechanism of information search in iCodes is to find information that potentially increases the coherence of the decision situation.[2]

Two other phenomena that have been described in the literature predict search behavior similar to the Attraction Search Effect: pseudodiagnostic search in hypothesis testing (Do-

[1]Both, Hart et al. (2009) and Fischer & Greitemeyer (2010) also discuss the role of accuracy motivation for selective exposure in their articles. Accuracy motivation is defined as the goal to search for information that leads to the objectively best choice. As the effect of accuracy motivation on selective exposure is at least somewhat inconsistent, Fischer & Greitemeyer (2010) put forward an integrative model that explains the combined influence of accuracy and defense motivation on selective exposure.

[2]The role of coherence for selective exposure has also been investigated by Fraser-Mackenzie & Dror (2009).

herty et al., 1979; Mynatt et al., 1993) and leader-focused search (Carlson & Guha, 2011). Pseudodiagnostic search describes that individuals tend to search for information about their current hypothesis only and fail to test the alternative hypothesis. This behavior is particularly observed when the first piece of found information supports the currently tested hypothesis (Mynatt et al., 1993). The aforementioned failure to test alternative hypotheses is problematic as a cue is only diagnostic for a hypothesis test when its values are known for both hypotheses.

In the case of leader-focused search, information-search behavior is also characterized as searching for information on the currently preferred option (the leader) independently of the expected valence of this information (Carlson & Guha, 2011). Carlson & Guha (2011) could show that this preference for information on the leader is so strong that subjects preferred negative information on the leader compared to negative information on the trailer (the currently less preferred option).

Similar cognitive explanations have been proposed for both pseudodiagnostic and leader-focused search. Evans et al. (2002) proposed that pseudodiagnostic search results from a habitual focus on one hypothesis only and individuals tend to ignore other, alternative hypotheses. Similarly, Carlson & Guha (2011) refer to *focalism* (Wilson et al., 2000) as a possible underlying mechanism for leader-focused search in that individuals focus on the current leader and subsequently ignore other options. Thus, besides different theoretical underpinnings, the only difference between leader-focused search and the Attraction Search Effect is that for the former effect subjects are asked which option is more attractive whereas for the latter effect the attractiveness of the options is manipulated via cue-value patterns. Both phenomena, pseudo-diagnostic and leader-focused search, are similar to the search pattern predicted by iCodes but lack an explicit theoretical model formalizing the underlying processes of this type of search behavior. With iCodes, there is now a computational, formal model that allows precise predictions of when and how strong the information search direction should be biased towards the currently more attractive option. Hence, our explanation does not contradict the theories mentioned above, but the observed focalism may be the result of an underlying coherence-maximizing mechanism.

When focusing on probabilistic-inference tasks, different models have been proposed that predict information search, such as heuristics as part of the adaptive toolbox (e.g., Gigerenzer & Todd, 1999; Payne et al., 1988) and models of the class of evidence accumulation models (e.g., Hausmann & Läge, 2008; Lee & Cummins, 2004). However, the prediction of the Attraction Search Effect is unique compared to these formalized models as they base only their prediction of the stopping of information search on the available information. The predicted direction of information search, however, in these types of models relies solely on external criteria such as the cues' validities. Yet, in iCodes, the information-search prediction depends on the additive effects of validity-driven cue-node activations and attractiveness-driven option-node activations on the activations of concealed cue-value nodes (Jekel et al., 2018). Thus, the Attraction Search Effect follows from the joint effects of validity and the current attractiveness of the options.

2.1.2 Evidence for the Attraction Search Effect

The Attraction Search Effect was tested by Jekel et al. (2018) in two experiments. In both experiments, they used an artificial stock-market game in which subjects had to choose the more successful of two stocks based on expert judgments that differed in their respective validities. For this stock-market game, the authors specifically designed half-open cue-value patterns that were highly diagnostic for the Attraction Search Effect. The diagnosticity of the patterns was achieved by creating two versions of each cue-value pattern such that in the first version (Version a) the Option A is more attractive than Option B and that in the second version (Version b) the Option B is more attractive than Option A. The change of attractiveness between the two versions was achieved by changing one or two cue values. With these two pattern versions, it was possible to calculate a qualitative Attraction Search Score that represents the difference of probabilities of behavior consistent with the Attraction Search Effect and behavior inconsistent with the Attraction Search Effect. Behavior was consistent with the Attraction Search Effect when subjects searched for the attractive Option A in Version a and behavior was inconsistent when subjects searched for the unattractive Option A in Version b of the cue-value patterns; $Attraction\ Search\ Score = p(Searching\ for\ Option\ A \mid Version\ a) - p(Searching\ for\ Option\ A \mid Version\ b)$. Thus, the Attraction Search Score is positive if subjects followed iCodes's predictions for information search and zero if subjects did not change their direction of search depending on the attractiveness of the options.

In the first experiment, Jekel et al. (2018) presented the half-open cue-value patterns to subjects and restricted information search to one piece of information. In the second experiment, Jekel et al. (2018) did not restrict information search but manipulated whether information search was costly or free. Both experiments show strong support for the Attraction Search Effect; though, the effect was less pronounced when information search was free. These initial results received further support in a reanalyses of five published experiments that also used a hypothetical stock-market game but were not specifically designed to test for the Attraction Search Effect. In addition, iCodes fit the observed information-search behavior quantitatively well and this fit depended on the influence of options' attractiveness in the model. Thus, there is initial support for iCodes's information-search predictions in probabilistic-inference tasks in the semantic context of an abstract and stylized hypothetical stock-market game.

3 The importance of model generalizability

With the recent extension of PCS-DM to iCodes and the presented empirical support for one of iCodes's core predictions, iCodes can be considered as a general theory for the decision process that incorporates information search, information integration, and decisions. As a general theory of decision making and information search, iCodes's predictions should be applicable to a broad range of different (multi-attribute) decision situations. A strict test of the applicability of a theory can be achieved by conducting a conceptual replication that varies experimental variables of the original studies (Makel et al., 2012). Conceptual replications ensure that the original results are not due to task or situational characteristics of the previous operationalizations but can be attributed with greater confidence to the processes specified by the theory (Bredenkamp, 1980). In our conceptual replications, we want to test whether iCodes's prediction for information-search behavior generalizes to different contexts.

In the previous studies testing iCodes, several aspects of the decision task have been kept constant that should be varied in a conceptual replication. One of these aspects is the semantic setting of the decision task. All experiments conducted and reanalyzed by Jekel et al. (2018) have used a probabilistic-inference task semantically set in a hypothetical stock-market scenario. The hypothetical stock-market game is a commonly used multi-attribute decision task (Bröder, 2003, 2000; Newell et al., 2003) that allows explicit control over different decision parameters, such as validities, and allows observation of information-search and decision behavior relatively unbiased by previous knowledge. Yet, at the same time and somewhat due to the high level of control, the hypothetical stock-market game is a highly artificial setting that lacks ties to the actual daily experiences of subjects. Further, a decision between stocks is only one instance of all possible decisions and such a neglect of stimulus sampling in an experiment is not only problematic with regard to the generalizability of results but also might dilute the validity of the causal inference (Wells & Windschitl, 1999). ICodes's predictions should, therefore, apply to a range of different and possibly more realistic semantic contexts. Testing different semantic contexts is especially relevant as prior work on leader-focused and pseudodiagnostic search has used a wide range of different decision contexts (Evans et al., 2002; Mynatt et al., 1993; Carlson & Guha, 2011). Thus, it is important to show that the Attraction Search Effect generalizes to different content domains as well.

Second, the cue-value patterns used to elicit the Attraction Search Effect have been kept constant between experiments. These patterns were specifically designed to be highly diagnostic for the Attraction Search Effect. However, as a general theory of decision making, iCodes's predictions should not be confined to a specific set of cue-value patterns but should be applicable in other cue-value constellations as well. The cue-value patterns have already been varied to some extent in the reanalyses of previously run studies in Jekel et al. (2018). These reanalyses have, however, all used the same context settings, namely a stock-market game.

A third aspect that was not varied between experiments is the way the information for the current decision task was presented. In all experiments, the cue values were presented in the matrix format of a typical mouselab task. Presenting information this way makes the relevant information highly accessible, facilitates information search itself, and might even influence the subsequent processing of information (Söllner et al., 2013). Yet, in many real-life decision tasks, the necessary information is often presented in a more complex fashion than in a matrix arranged according to cue validity. Thus, in order to claim that iCodes is general theory of decision making, it is important to show that the Attraction Search Effect still emerges when information is structured differently.

The current experiments successively relaxed the restrictions inherent in Jekel et al. (2018) demonstrations of the Attraction Search Effect. First, we extended the semantic contexts to various decision domains beyond the stock-market game in all three experiments, using 13 different decision contexts altogether. Second, we also used cue-value patterns different from the original ones (Experiment 2). Finally, we disposed of the commonly used restrictive matrix format of information presentation that is prevalent in many studies investigating information search in decision making (Experiment 3). By relaxing many of the restrictions inherent in Jekel et al.'s (2018) original experiments, we aim to replicate the Attraction Search Effect in different decision contexts and thus test the limits of its generalizability.

4 Experiment 1: Extension to different decision domains

The first experiment used cue-value patterns from the experiments by Jekel et al. (2018) but in a selection of six different semantic contexts. As we are interested in whether iCodes can predict information search in different contexts, we will concentrate solely on information search as the dependent variable in this and the following experiments. Thus, we will not analyze subjects' choices.

4.1 Method

4.1.1 Materials

Content scenarios. We constructed six different content scenarios for the decision task that represented mainly preferential decisions. These scenarios ranged from choosing a hotel to deciding which weather forecast to trust when planning a trip. One of the scenarios is the task to choose which of two cities is larger, commonly known as *city size task*, and was added to relate to earlier research (e.g., Gigerenzer & Todd, 1999). For every scenario, we chose four cues relevant to this decision. As the validity of these cues is mostly subjective, cues were ordered by our assumed importance for each scenario. To validate our assumptions, subjects were asked after the task for their subjective rating of importance of the cues. The content scenarios and the respective cues are displayed in Table A1 in Appendix 7.2. To make the decision task less abstract, we further changed the format of the cue values from "+" and "−" to different pictoral formats, such as a five- vs. two-star ratings, thumbs-up vs. thumbs-done icons, or "yes" vs. "no" icons for the city size scenario.[3]

Cue patterns. In this experiment, we used a subset of the original cue-value patterns from Jekel et al. (2018). Jekel et al. (2018) designed their cue-value patterns in pairs such that two versions of the same pattern differed in one or two cue values, so that either Option A or Option B was more attractive (see Table 1). For the present experiment, we selected three cue patterns from Jekel et al.'s (2018) studies. Pattern 3 was selected because it illicited the strongest Attraction Search Effect in Jekel et al.'s (2018) studies, with an Cohen's *d* ranging from 0.81 to 2.66. Patterns 1 and 2 showed the third and fourth strongest Attraction Search Effect, respectively, in the original studies, with Cohen's *d* ranging from 0.22 to 1.15 and from 0.61 to 0.92, respectively. These cue-value patterns were chosen to increase our chances to find an Attraction Search Effect under more relaxed experimental conditions.

4.1.2 Measures

Subjective importance of cues. To assess the subjective importance of the cues, subjects were asked to rate each cue on how important they thought the cue was for their decision on a scale from 0 to 100, with zero representing *not important at all* and 100 representing *extremely important*. The purpose of this measure was to check whether the assumed validity ordering corresponded to the actual importance ordering by subjects.

Table 1: Version a and Version b of cue patterns used in Experiment 1.

	Pattern 1		Pattern 2		Pattern 3	
	A	B	A	B	A	B
Cue 1	?	−(+)	+(−)	?	+(−)	−(+)
Cue 2	−	?	+(−)	?	?	?
Cue 3	+	−	?	?	+	−
Cue 4	−	+	?	?	−	?

Note. + = positive cue value, − = negative cue value, ? = hidden, searchable cue value; Version a of patterns is displayed, cue values in parentheses are from Version b. Patterns 1, 2, and 3 correspond to Patterns 4, 5, and 7, respectively, in Jekel et al. (2018).

Attraction search score. Just as in the study by Jekel et al. (2018), we computed the individual Attraction Search Scores as the difference of the probability of searching for Option A in Version a vs. in Version b across the three cue-value patterns, $Attraction\ Search\ Score = p(Searching\ Option\ A|Version\ a) - p(Searching\ Option\ A|Version\ b)$.[4] As mentioned above, the first probability represents the probability of behavior consistent with the Attraction Search Effect, whereas the second probability represents the probability of behavior inconsistent with the Attraction Search Effect. Thus, if the Attraction Search Score is larger than zero, subjects show more behavior in line with the Attraction Search Effect.

4.1.3 Design and procedure

Each subject was presented with each of six content scenarios and with each of the six patterns (three patterns in two versions each). To avoid large trial numbers which are suboptimal for online studies, the variable Scenario with six levels and the variable Pattern with six levels (three pattern with two versions each) were balanced using a latin square design which resulted in six experimental groups. Therefore, each experimental group was exposed to every pattern and every content scenario. After opening the online study and agreeing to an informed consent, subjects provided demographic information before working on the actual task. In each of the six trials subjects were familiarized with the decision context and could then search for one piece of additional information. A picture of the task setup can be found in Figure 2. After seeing the additional piece of information, subjects had to choose one of the options. When the decision task was completed, subjects filled out the subjective importance measure for each of the scenario's cues.

[3] All instructions and decision scenarios can be found in the supplementary materials.

[4] As we presented each cue-pattern in both versions once, there are three observations of Version a and three observations of Version b for each

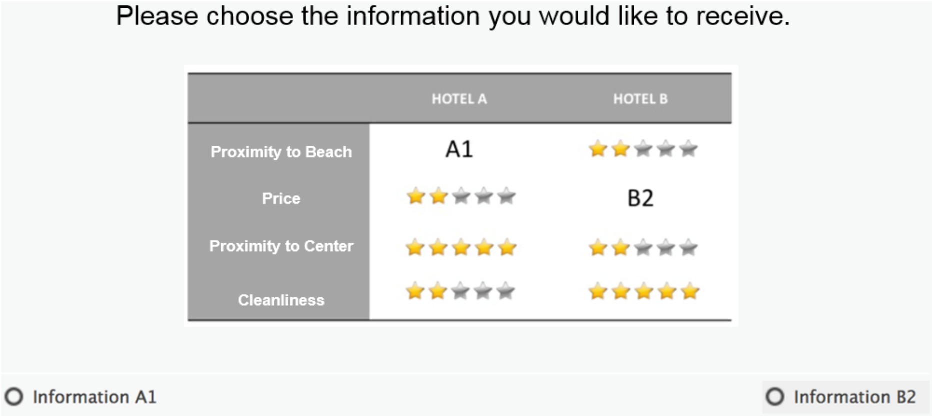

FIGURE 2: A translated (from German) screenshot of the decision task in Experiment 1. The current cue-value pattern is Pattern 1 in Version a. Subjects could search for information by selecting the radio button for the corresponding piece of information in the matrix. On the next screen, the searched-for information appeared in the decision matrix and subjects could choose one of the options.

4.1.4 Subjects

The online experiment was conducted with the program *Unipark* (Questback, 2016). Subjects were recruited online via the registration system of the University of Mannheim and via online platforms such as Facebook research groups. The data collection yielded a sample of 303 subjects (201 female, 47.5 % university students, $M_{age} = 33.7$, $SD_{age} = 15.5$, age range 17–70). Subjects could decide whether they participated for course credit or entered a lottery to win a 15€ online-shop gift certificate.

4.2 Results

All following analyses were conducted with R (R Core Team, 2019). All plots were created by using the *ggplot2* package (Wickham, 2016), mixed model analyses were run with the packages *lme4* (Bates et al., 2015) and *lmerTest* (Kuznetsova et al., 2017).

To test for the Attraction Search Effect, we tested whether the Attraction Search Score was significantly larger than zero. The mean Attraction Search Score of subjects was $M_{ASS} = 0.32$ and was significantly larger than zero, $t(302) = 14.55$, $p < .001$, $d = 0.84$ (see Figure 3 for the distribution of individual Attraction Search Scores in all experiments). We also looked at the Attraction Search Scores per cue-value pattern.[5] The Attraction Search Score was also significantly larger than zero when looking at the three patterns separately, $M_{Pattern1} = 0.25$, $t(302) = 6.06$, $d = 0.35$, $M_{Pattern2} = 0.26$, $t(302) = 8.29$, $d = 0.48$, and $M_{Pattern3} = 0.46$, $t(302) = 13.62$, $d = 0.78$, all $ps < .001$. Note, however, that comparing the Attraction Search Scores of the separate patterns required comparing across different scenarios. To account for this, we also calculated the Attraction Search Scores for each scenario across subjects.[6] As shown in Figure 4, all scenario-wise Attraction Search Scores were above zero; however, there was substantial heterogeneity in the sizes of the scenario-wise Attraction Search Scores.

One explanation for the heterogeneity of the Attraction Search Scores on the scenario level might be that our assumed subjective importance of cues did not match subjects' subjective importance. Looking at the subjective importance ratings, our assumed ordering of cues was mostly matched by the importance ratings of subjects. Subjects' mean subjective importance ratings can be found in Table A1 in the Appendix 7.2. Substantial differences occurred in the *Hotel* scenario, in which subjects considered the last cue as most important. Further, in the *Job* and in the *City Size* scenarios, subjects considered the second cue as more important than the first, more so for the *City Size* scenario.

As the Attraction Search Score aggregated over subjects and content scenarios, we also ran a generalized linear mixed model analysis to investigate the variation across these variables. In this model, the dependent variable was whether subjects searched for Option A in any given trial. The effect-coded predictor in this model was whether Option A was attractive in this trial (Version a; +1) or not (Version b; −1). A significant, positive regression weight for the predictor *version* would indicate an information-search pattern consistent with the Attraction Search Effect. To account for

subject.

[5]As every subject saw each version of every cue-value pattern only once, this analysis rested on only one trial of Version a and one trial of Version b for each pattern and each subject.

[6]As there were no within-subjects repetitions of scenarios, this method resulted in one Attraction Search Score per scenario only and therefore did not allow any statistical inferences about whether the Attraction Search Score for each scenario was larger than zero.

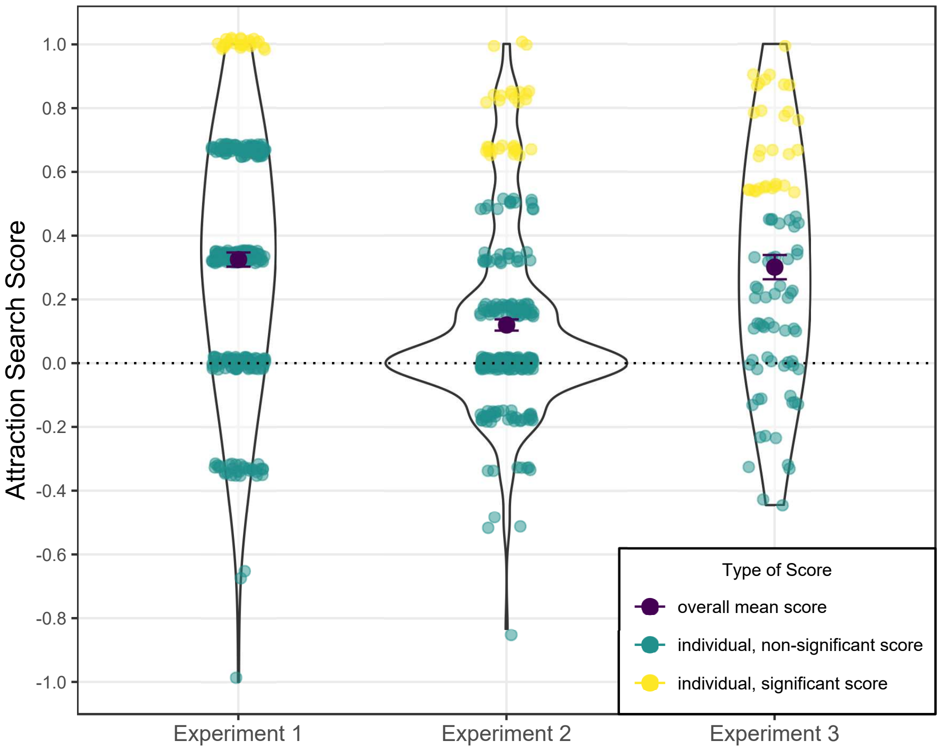

Figure 3: Distribution of individual Attraction Search Scores in all three experiments. The violet points represent the mean Attraction Search Score in each experiment and error bars the standard errors of those means. Attraction Search Scores of zero indicate information search that is independent of the currently available evidence. Thus, every data point above zero indicates that an individual showed a tendency to search for information on the currently attractive option. Yellow points indicate individuals showing a significant ($p < .050$) score at the individual level according to a one-tailed binomial test. The number of trials required for significance is 6 out of 6, 12 out of 14, and 14 out of 18 in Experiments 1–3, respectively.

variation in the data, we implemented a maximum random effects structure with random intercepts for subjects and content scenarios, as well as random slopes for *version*.

The results of this generalized linear mixed model showed that subjects were in general more likely to search for information on Option A given that this option was attractive, $\beta = 0.75$, $SE = 0.11$, $z = 6.77$, $p < .001$ (see Table B1 and Table B2 for all model estimates). More precisely, the probability of searching information for Option A increased from 21.7% in Version b to 55.5% in Version a of the patterns. The effect of pattern version varied across subjects as well as content scenarios (see Figure 6). Specifically, the heterogeneity of the content scenarios matched the one we observed in the aggregated results.

To check whether we could explain some of the heterogeneity when accounting for differences due to cue-value patterns, we added a Helmert-coded *cue pattern* predictor to the mixed model[7] as well as the interaction of *cue pattern* and *version*. The effect of *version* remained positive and significant, $\beta = 0.88$, $SE = 0.13$, $z = 6.84$, $p < .001$. Additionally, there was a significant effect that subjects were less likely to search for Option A when faced with Pattern 2 than when faced with Pattern 1, $\beta = -0.80$, $SE = 0.07$, $z = -10.75$, $p < .001$. Further, the effect of *version* on information search depended on *cue pattern*, such that the *version* effect was the most pronounced for Pattern 3 when comparing it to the other two cue-value patterns, $\beta = 0.15$, $SE = 0.04$, $z = 3.72$, $p < .001$. There also was a larger effect for Pattern 1 compared to Pattern 2, $\beta = 0.16$, $SE = 0.07$, $z = 2.14$, $p = .032$.

4.3 Discussion

The first experiment shows strong support for the Attraction Search Effect in semantic contexts different from the hypothetical stock-market game originally used by Jekel et al. (2018). Subjects tended to search for information about the more attractive option in all of the three cue-value patterns as

[7]With the Helmert-coding, two predictors were added to the model: one, comparing Pattern 3 (+2) against Pattern 1 (−1) and 2 (−1), and therefore comparing the cue-value pattern with the strongest effect against the other two cue-value patterns. The other predictor compared Pattern 2 (+1) against Pattern 1 (−1).

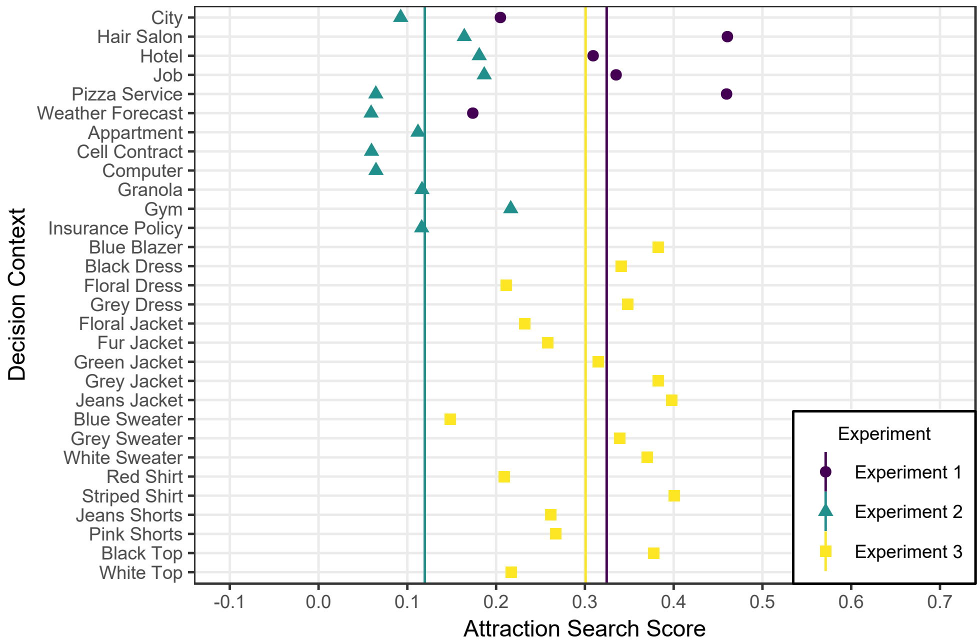

FIGURE 4: Distribution of Attraction Search Scores for each decision context in all three experiments. The lines represent the mean Attraction Search Scores across subjects and scenarios in the respective experiments.

well as in every content scenario. The effect sizes as well as the absolute Attraction Search Scores overall and for the separate cue-value patterns mirror those from Jekel et al. (2018) in their study without information search costs (for the Attraction Search Scores in Jekel et al. (2018) experiments see Figure 5).

Our mixed model analyses reveals that the strength of the Attraction Search Effect differs between individuals as well as semantic contexts. The differences in effect size for the semantic contexts might be due to the fact that our assumed subjective importance ordering did not always match those of subjects. This assumption is supported by the fact that among the weakest predicted effects for decision context are the City and the Hotel Scenario.[8] Both semantic contexts showed on average a different ordering in subjects' importance ratings. In sum, we replicated the results from Jekel et al. (2018) in a more diverse setting, however, while still using the cue-value patterns that were specifically designed to elicit the Attraction Search Effect. Therefore, it is an important next step to show that the Attraction Search Effect can be found with different cue-value patterns.

[8]A mixed logistic regression directly investigating the effect of subjective importance orderings on the Attraction Search Effect is reported in Appendix 7.2. It includes the individual rank correlations of the intended and the individually rated cue order per scenario and hints at a moderating effect of the ordering of importance ratings on the Attraction Search Effect. However, see also Appendix 7.2 for a caveat of this analysis.

5 Experiment 2: Extension to different cue patterns

In the second experiment, we extended the results from the first experiment by testing whether the Attraction Search Effect can be found in more diverse semantic contexts and even without using specifically designed, highly diagnostic cue patterns. Therefore, we did not present any information before search and manipulated only the valence of the first cue value subjects searched for while randomizing the valence of the remaining cue values. This experiment and the respective hypothesis were preregistered (Open Science Framework; Scharf et al., 2017, osf.io/j7vg4).

5.1 Method

5.1.1 Materials

In addition to the six decision scenarios used in the first experiment, we developed six further decision contents, ranging from renting a new apartment to deciding on a new gym or to buying a new computer (all scenarios and cues can be found in Table 2).

We presented a completely closed mouselab matrix to our subjects. In this matrix, the valences for all but the first opened cue values were randomly assigned. The valence of the first searched-for cue value was counterbalanced, to achieve an experimental manipulation of the attractiveness of options. This manipulation thus ensures that in six of the

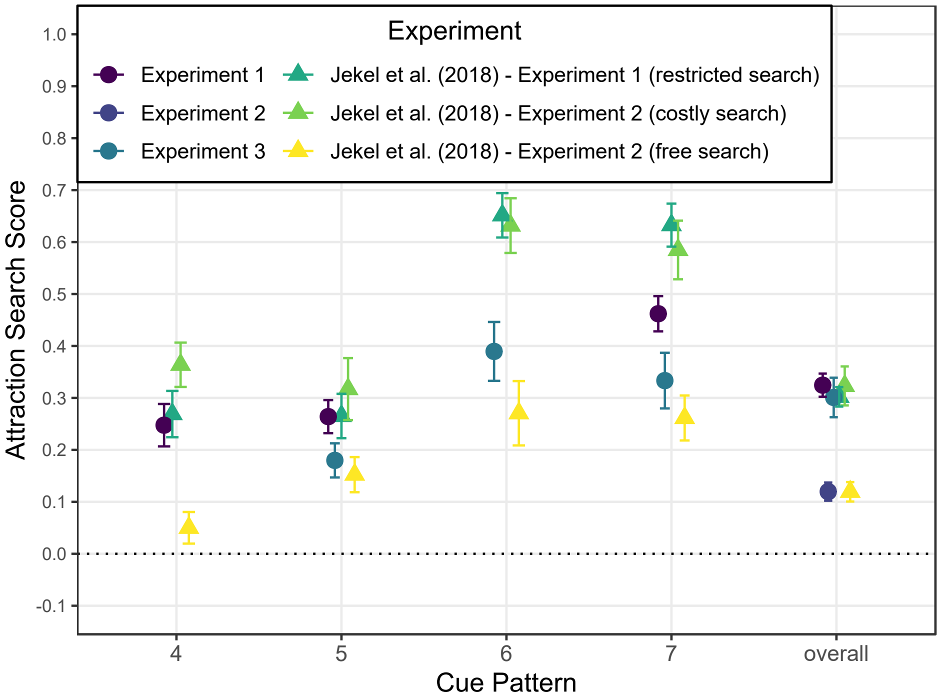

FIGURE 5: Mean Attraction Search Scores for each cue-value pattern and overall from all three experiments in comparison with the Attraction Search Scores from Jekel et al. (2018). The triangles represent the mean Attraction Search Scores from the first two studies by Jekel et al. (2018) for each pattern and overall. Cue-pattern names on the x axis are the original names from Jekel et al. (2018): Patterns 4, 5, and 7 correspond to Patterns 1, 2, and 3 in Experiment 1, respectively; Patterns 5, 6, and 7 correspond to Patterns 1, 2, and 3 in Experiment 3, respectively.

twelve trials the first searched-for cue value yielded positive information (and thus made the first searched-for option attractive) whereas in the other six trials the first searched-for cue value yielded negative information (and thus made the first searched-for option unattractive). It is important to note that it did not matter which specific piece of information subjects searched for first for this manipulation to take effect.

To control whether subjects complied with instructions and read the decision scenarios, we included a decision scenario recognition test. After subjects completed the decision trials, they were asked to identify on which topics they had just decided. For this purpose, they were shown six out of the twelve original decision scenarios and six distractor scenarios. If they answered more than two scenarios incorrectly, subjects were excluded from analysis.

5.1.2 Measures

As we did not use the cue-value patterns from the original study by Jekel et al. (2018), we computed the individual Attraction Search Scores as the difference of the probability of switching options between the first and the second information search across subjects and scenarios when the initial evidence was negative vs. positive; $Attraction\ Search\ Score = p(switching\ options|initial\ negative\ information) - p(switching\ options|initial\ positive\ information)$.[9] Switching options when the initially found evidence is negative is consistent with the Attraction Search Effect, while switching options when the initially found evidence is positive is inconsistent search behavior. Therefore, as in the first experiment, if the Attraction Search Score is larger than zero, subjects show more behavior in line with the Attraction Search Effect.

5.1.3 Design and procedure

We manipulated the valence of the first clicked-on cue value (positive vs. negative) within-subjects. As Jekel et al. (2018) showed that the Attraction Search Effect is stronger when information search is costly, we additionally tried to induce a sense of search costs by restricting the number of possible searches per trial (either three, five, or seven searches). We opted for restricting information search instead of implementing explicit search costs, as implementing monetary search costs is difficult in preferential decision tasks, especially with hypothetical tasks conducted online. Since the Attraction Search Effect requires available information to

[9]The probabilities were calculated based on six trials with initial positive information and six trials with initial negative information for each subject.

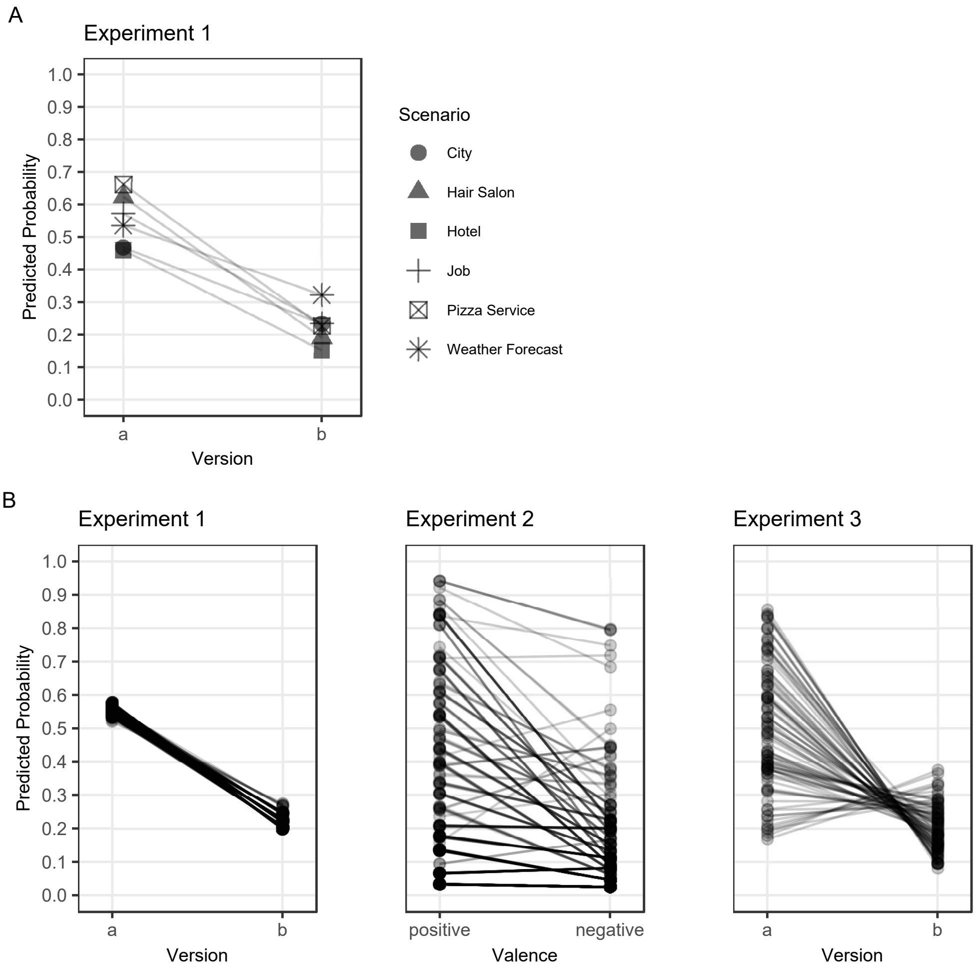

FIGURE 6: Predicted probabilities of searching for Option A (Experiment 1 and 3) or of searching for the same option (Experiment 2) based on random slopes of mixed logistic regression analyses. The plot under A represents the random slope for the different decision scenarios in Experiment 1, the plots under B represent the random slopes for subjects in all three experiments. These plots can be read as follows: the more negative the slope between Version a and b (or positive and negative initial valence in Experiment 2, respectively), the stronger the predicted Attraction Search Effect for this scenario or subject.

take effect, restricting search to one piece of information as in the original experiments by Jekel et al. (2018) is not possible in a completely closed matrix. In order to restrict information search and at the same time to avoid subjects immediately opening the fixed amount of information granted to them, we opted for restricting information search variably from trial to trial without subjects knowing beforehand how much information they could open in this specific trial. This way, every piece of information subjects chose to open during a trial should rationally be the most informative piece of information they could choose, as it could be their last piece of information. Therefore, subjects were not informed about the restriction of search before starting a trial but were only informed whenever they opened the maximal number of possible information for the trial. It is important to note that information search was restricted only in the sense that subjects could not open more information — they were free to search for less information than the allowed amount per trial given they opened at least one cue value.

The order of trials and thus the valence of the first cue value and the amount of search was randomized for each subject. After following the link to the online study, subjects first gave their consent for participating in the study. Following a practice task, subjects started working on the actual decision trials. Before each trial, subjects were presented with a brief introduction into the ensuing content scenario. Subjects had to open one piece of information in every trial. They could then search for either two, four, or six additional pieces of information; however, they did not know how many pieces of information they could search for in a specific trial.

Table 2: Additional content scenarios and cues in Experiment 2.

Granola	**Gym**
Amount of Dietary Fiber	Monthly Pay
Number of Calories	Offered Courses
Proportion Organic Ingredients	Equipment
Proportion Fairtrade Ingredients	Opening Hours
Computer	**Apartment**
Price	Proximity to City Center
Speed	Sufficient Lighting
Design	Square Footage
Loudness	Friendliness of Neighbors
Insurance Company	**Cell Contract**
Coverage	Monthly Pay
Monthly Pay	Network Reception
Accessibility in Case of Damage	Number of Free Minutes
Customer Friendliness	Data Volume

Note. Scenario names are printed in bold font, the four cue names are printed underneath the respective scenario name.

When subjects reached the limit of searchable information in a trial, they were informed that they could no longer search for additional information and that they had to decide now (for an example trial of the decision task see Figure 7). After completing all 12 trials, subjects had to work on the recognition task, in which they had to identify six of the original content scenarios among a list with additional six distractor scenarios.[10] After finishing this task, subjects went on to provide some demographic details about themselves and then could decide whether they wanted to receive course credit; participate in the lottery, in which they could win one of ten 10€-online shop gift certificates; or neither of these two options. Finally, subjects were debriefed and thanked for their participation.

5.1.4 Subjects

An a-priori power analysis assuming $\alpha = \beta = .05$ for a one-tailed one sample t test and a small Attraction Search Effect with a Cohen's $d = 0.20$ yielded a sample size of 272 subjects (Faul et al., 2007). Due to expected dropout, a sample of 300 subjects was aspired to collect. The stopping rule was to either stop data collection after two months or when 300 subjects were collected. The study was programmed with *lab.js* (Henninger et al., in press) in conjunction with the *Multi-Attribute Decision Builder* (Shevchenko, 2019). The original sample included 305 completed data sets. From these 305 subjects, eight subjects were excluded because data were not saved for all of the twelve decision trials. Thus, the complete sample included a sample of 297 subjects (230 female, 1 other, $M_{age} = 22.9$, $SD_{age} = 5.6$). Seventeen subjects were excluded because they answered more than two questions incorrectly in the recognition test. After exclusion, a total of 280 subjects remained in the final sample (217 female, 1 other, 84.6% university students). The mean age of the sample was $M_{age} = 22.8$ ($SD_{age} = 5.6$, range 18–63).

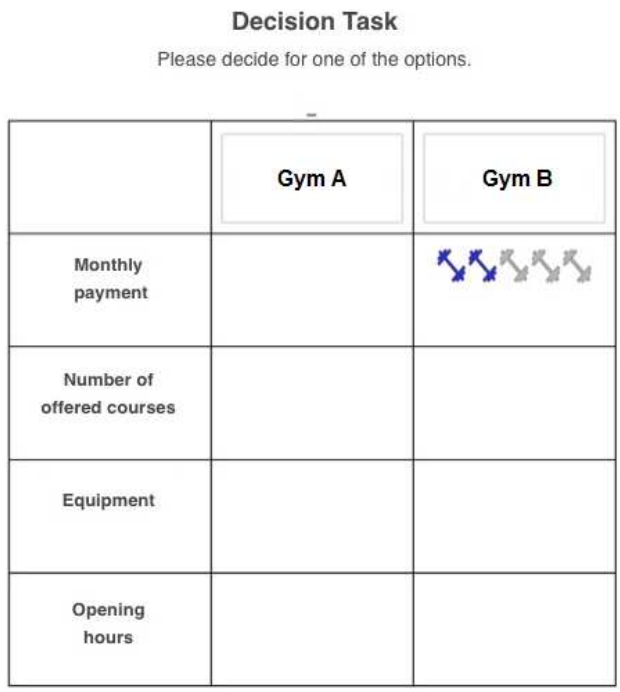

Figure 7: A translated screenshot of the decision task in Experiment 2. In the current trial, the valence of the first opened information was negative (2 of 5 dumbbells). Subjects could search for information by clicking on the empty boxes in the matrix. Then the respective cue value would appear. Afterwards, they chose one of the options by clicking on the button around the options.

5.2 Results

5.2.1 Preregistered analyses

To test whether the Attraction Search Effect emerged in a preferential decision task without specifically designed patterns, we calculated the Attraction Search Score for each subject over all trials. As predicted, the Attraction Search Score was significantly larger than zero $M_{ASS} = 0.12$, $t(279) = 6.82$, $p < .001$, Cohen's $d = 0.41$. Thus, we

[10] Due to an error in the programming of the experimental software, some subjects were presented with only five distractors and seven targets instead of six of each. As there is no difference in performance in the recognition task between subjects who saw seven targets and subjects who saw six targets, we still used the recognition test data for exclusion, $M_{correct,6targets} = 0.96$, $M_{correct,7targets} = 0.95$, $t(284.41) = 0.73$, $p = .464$

found evidence for the Attraction Search Effect in different semantic contexts and closed cue-value patterns.

5.2.2 Additional exploratory analyses

To compare the heterogeneity between decision scenarios to the first experiment, we also calculated the Attraction Search Scores for each scenario across subjects. As shown in Figure 4, all scenario-wise Attraction Search Scores were above zero and there was less heterogeneity between scenarios compared to Experiment 1.

To account for the multi-level structure of the data and to explore the heterogeneity between scenarios further, we also ran a generalized linear mixed model analysis comparable to that in Experiment 1. In this model, the dependent variable was whether subjects continued to search for the same option as in their first search in any given trial. The predictor was whether the valence of the first opened cue value was positive or negative. Again, a significant, positive regression weight for the predictor *valence* would indicate an information-search pattern consistent with the Attraction Search Effect. To account for variation in the data, we implemented a model with random intercepts for subjects and content scenarios as well as a random slope for *valence* for subjects.[11]

The results of this generalized linear mixed model showed that subjects were in general more likely to stay with the searched-for option when the first opened cue value was positive, $\beta = 0.38$, $SE = 0.11$, $z = 3.58$, $p < .001$ (see Table B1 and Table B2 for all model estimates). Specifically, the probability of staying with the searched-for option increased on average from 6.5%, when the first opened cue value was negative, to 12.9%, when the first cue value was positive. The results for the random effects showed considerable variance of the effect of *valence* between subjects (see Figure 6).

Looking at the distribution of the Attraction Search Score values in Figure 3 and the heterogeneity of the individual effects in the mixed model, it was apparent that there is a large proportion of subjects that did not show the Attraction Search effect. In fact, the median of the overall Attraction Search Score distribution was $Md_{ASS} = 0$. One difference between subjects with an Attraction Search Score of zero and subjects with a non-zero Attraction Search Score was the amount of searched cue values. Subjects with an Attraction Search Score of zero tended to search for more cue values, $M_{ASS=0} = 4.72$, than subjects with a non-zero Attraction Search Score, $M_{ASS\neq 0} = 4.57$, $t(277.09) = -2.61$, $p = .010$, Hedge's $g = -0.31$. Additionally, we found that subjects with higher individual Attraction Search Scores tended to take longer to open the first cue value, $r(278) = .341$, $p < .001$.

To further investigate subjects who had an Attraction Search Score of zero, we hypothesized that some subjects used predetermined, fixed search strategies. To test this assumption, we formulated three different search strategies: strictly cue-wise, lenient cue-wise, and strictly option-wise information search.[12] The strictly cue-wise search was defined as subjects starting to search for information on one option's side, continuing their search on the same cue on the other option's side, and then returning to the first option's side for the ensuing search and so on. The lenient cue-wise search also was defined as always searching for two pieces of information from the same cue consecutively but did not require to always start the search on the same option. The strictly option-wise search was defined as searching information on one option until all information for this option was acquired and then switching to the other option. On average, subjects used a strictly cue-wise search strategy in 39.1% ($SD = 25.0$), a lenient cue-wise search strategy in 23.7% ($SD = 17.9$), and an option-wise search strategy in 7.1% ($SD = 14.2$) of trials. In 30.1% ($SD = 23.4$) of trials, subjects' information-search pattern could not be classified as belonging to one of the aforementioned strategies. Thus, in over half of all trials some kind of fixed cue-wise search strategy was used.

In order to test whether the occurrence of Attraction Search Scores of zero could be explained by subjects using predetermined search strategies, we correlated the individual Attraction Search Scores with the number of trials of each subject belonging to one of formulated search strategies. Indeed, the correlation of individual Attraction Search Scores and the number of trials in which subjects searched strictly cue-wise was negative, $r = -.31$, $n = 280$, $p < .001$; indicating that subjects who searched for information strictly cue-wise in more trials had lower Attraction Search Scores. The results were similar for the lenient cue-wise strategy for which the correlation was negative as well, $r = -.16$, $n = 280$, $p = .008$. For the number of trials searched following an option-wise strategy, we found a positive correlation, $r = .28$, $n = 280$, $p < .001$. The correlation between the number of unclassified trials per subject and the individual Attraction Search Scores was also positive, $r = .28$, $n = 280$, $p < .001$. Therefore, subjects with a low Attraction Search Score had a stronger tendency to search for information consistent with a pre-determined, cue-wise search strategy.

To analyze the influence of strategies on the trial level, we ran the same mixed logistic regression as described above and added the count of trials following any of the above-

[11]The maximum random model structure did not converge. This random effects structure was achieved by starting with the maximum random structure, then to first exclude correlations between random effects and then to remove the random slope(s) with the smallest variance until the model converged.

[12]We did not calculate the often used Payne Index (Payne, 1976), as this index is biased if the number of options is not equal to the number of cues (Böckenholt & Hynan, 2006).

mentioned strategies as a predictor.[13] In this model, the probability of searching for the same option was 12.6% when finding initial positive evidence compared to 6.2% when finding initial negative evidence, $\beta = 0.38$, $SE = 0.11$, $z = 3.63$, $p < .001$ (see Table B1 and Table B2 for all model estimates). Additionally, the more trials in which a subject showed information-search behavior that followed a specific strategy the less likely she was to continue to search for the same option, $\beta = -0.41$, $SE = 0.04$, $z = -9.99$, $p < .001$. The number of trials following a search strategy also influenced the strength of the effect of the first opened cue value, $\beta = -0.09$, $SE = 0.03$, $z = -2.71$, $p = .007$. This interaction took the effect that if no strategy was used in any trial, the predicted probability of searching for the same option when the initial information was positive was 90.4% compared to 51.0% when the initial information was negative. On the other hand, when an information search strategy was used in every trial, the predicted probability of searching for the same option was 2.3% when the initial information was positive and 2.0% when the initial information was negative. Note that the overall effect of searching with a strategy was negative because cue-wise search strategies, which had a negative effect on the Attraction Search Score, were much more common (in total 62.8% of trials) than option-wise search strategies (7.1% of trials), which had a positive effect on the Attraction Search Score.

5.3 Discussion

In the second experiment, we took a step further away from the original setup of Jekel et al. (2018) by extending the range of semantic contexts and using closed cue-value patterns with randomized cue values. The results show that the Attraction Search Effect emerges under these conditions as well and, thus, does not appear only when using highly diagnostic cue-value patterns. Further, in contrast to the first experiment, the effect of the valence manipulation did not differ between decision contexts and there were systematic differences only in how likely subjects were to continue to search for the same option in different contexts. The systematic differences in the valence effect between different scenarios might be absent because in this experiment the prediction of the Attraction Search Effect did not require the subjects to have the correct subjective importance ordering. Rather, we assumed that the first opened cue is likely to be the most valid cue.

We did observe a considerable drop in effect size in the second experiment compared to the first. This drop is due to a large number of subjects who had an Attraction Search Score of zero. This finding is also supported by the large variability due to subjects in the mixed model analysis. The heterogeneity can partly be explained by looking at subjects' search behavior: Subjects with Attraction Search Scores of zero tended to search for more information. Additionally, subjects with lower Attraction Search Scores tended to open the first cue value faster and searched for information in a cue-wise fashion in more trials. The results of the mixed logistic regression corroborate these findings by showing that the Attraction Search Effect is weakened the more subjects followed specific information search strategies on the trial level. Taken together, these exploratory results show similarities to Jekel et al.'s (2018) results in the condition without search costs. Jekel et al. (2018) showed that subjects searched for more information faster and that individual Attraction Search Scores were considerably reduced when no information search costs were implemented. Thus, the results of Experiment 2 indicate that the restriction of search might not have been strong enough to induce a sense of search costs.

Besides the aforementioned limitations, we still found a medium-sized Attraction Search Effect in an experiment that did not rely on a specific semantic context or specifically designed cue-value patterns. Thus, the results of this experiment emphasize the overall robustness of the effect and the range of applicability of iCodes.

[13]The individual count was mean-centered across subjects for this analysis.

Table 3: Version a and Version b of cue patterns used in Experiment 3.

	Pattern 1		Pattern 2		Pattern 3	
	A	B	A	B	A	B
Cue 1	+(−)	?	+(−)	−(+)	+(−)	−(+)
Cue 2	+(−)	?	?	?	?	?
Cue 3	?	?	+	−	+	−
Cue 4	?	?	−	+	−	?

Note. + = positive cue value, − = negative cue value, ? = hidden, searchable cue value; Version a of patterns is displayed, cue values in parentheses are from Version b. Patterns 1, 2, and 3 correspond to Patterns 5, 6, and 7, respectively, in Jekel et al. (2018).

6 Experiment 3

Experiment 3 varied another aspect of the decision task that has been kept constant in Jekel et al.'s (2018) studies and in our studies so far: the way in which information is presented. Until now, every experiment testing the predictions of iCodes has used the matrix presentation of the classic mouselab task. It has been shown that the way information is presented influences information-search behavior (Bettman & Kakkar, 1977; Ettlin et al., 2015). Presenting information in a matrix organizes the information for the decision maker and this organization in turn influences search behavior (Schkade & Kleinmuntz, 1994). Thus, in this experiment we test whether the Attraction Search Effect still emerges in a quasi-realistic online shop setting. The subjects' task in this experiment was to imagine being a buyer for an online clothing shop and to buy clothes online. In addition, as the two previous experiments were both run in German and with German samples, we decided to collect data from a different, non-German subject pool via the platform Prolific (Palan & Schitter, 2018). This experiment and our hypothesis were preregistered (Open Science Framework; Scharf et al., 2018, osf.io/nfruq).

6.1 Method

6.1.1 Materials

Cue patterns. As in Experiment 1, we again used a subset of the original cue-value patterns from Jekel et al. (2018). As described above, each pattern has two versions that differ in which option is currently more attractive. For this experiment, we selected three from the original eight patterns, displayed Table 3. Pattern 2 and Pattern 3 were chosen because they elicited the strongest and the second strongest Attraction Search Effect in the original studies. Pattern 1, which elicited the fourth strongest Attraction Search Effect in the original studies, was chosen to include a pattern that showed a strong effect but at the same time has more than three searchable cue values. Thus, the addition of Pattern 1 was supposed to increase the variability between patterns. Each pattern in both versions was presented three times, leading to a total number of 18 trials per subject.

Shop items. We used images of 18 different items of clothing for this experiment. These articles of clothing were each described by customer ratings on four attributes. Subjects were told that these attributes differed in their relative importance for the online shop they are shopping for. The attributes in the order of their importance were the fit of the clothes, the comfort of the fabric, the availability of sizes, and the ease of care. The customer ratings were dichotomized, such that a negative overall rating of one of the attributes was described by two stars and a positive overall rating was described by five stars. To increase the realism of the online shop, each item was assigned a fictional brand name (four-letter pseudowords adapted from Stark & McClelland, 2000) and a fictional brand logo. In each trial, subjects had to decide between the same article of clothing that differed in their brands and the customer ratings of their attributes only. An example trial is displayed in Figure 8.

6.1.2 Measures

Just as in Experiment 1, we computed the individual Attraction Search Scores as the difference of the probability of searching for Option A in the nine trials of Version a vs. of Version b across articles of clothing, $Attraction\ Search\ Score = p(Searching\ Option\ A \mid Version\ a) - p(Searching\ Option\ A \mid Version\ b)$.[14]

FIGURE 8: A screenshot of the decision task in Experiment 3. The current cue-value pattern is Pattern 3 in Version b. Subjects could search for information by clicking on the number under the cue name. The number indicated the importance of the cue for the decision, with "1" representing the most important attribute and "4" representing the least important attribute. Then the respective cue value would appear. Afterwards, they chose one of the options by clicking on its "Add to cart" button.

6.1.3 Design and procedure

All subjects were presented with all cue-value patterns in both versions and all shop items in a total of 18 trials (3 cue-value patterns x 2 pattern versions x 3 repetitions). Note that the cue patterns were repeated but not the items of clothing. The order of trials as well as the combination of cue-value patterns, shop items, logos, and brand names were randomized for each subject. We further balanced presentation of the cue-value patterns for the repetitions, such that Option A of each pattern was once on the left side, once on the right side, and assigned to a side randomly for the third repetition. The online experiment was programmed in *lab.js* (Henninger et al., in press) and run via the platform Prolific (Palan & Schitter, 2018). Subjects received £1.10 for their participation. Before working on the actual task, subjects agreed to an informed consent form and read the instructions for the task.

Subjects were asked to imagine that they work as a buyer for an online clothing shop and that their task was to choose

[14] Due to the three repetitions of each cue pattern, Version a and Version b were each presented nine times.

18 different articles of clothing in order to restock their employer's warehouse. We included three questions about the instructions that had to be answered correctly before the subjects could continue with the actual task. The number of repetitions it took to answer these questions correctly were used as an exclusion criterion, such that when subjects had to repeat these questions more then once they were excluded from analysis. During the task, subjects were allowed to search one additional piece of information, after which they had to decide which article of clothing they wanted to buy. Before finishing the study, subjects were asked to provide some demographic information and were then thanked for their participation.

6.1.4 Subjects

In a student project conducted to pretest the materials, we found an Attraction Search Effect with an effect size of Cohen's $d = 1.34$ with $N = 312$. As the current experiment was run in a non-German and likely more diverse sample, we decided to be rather conservative for our sample-size rationale. A sensitivity analysis revealed that we could find an effect of Cohen's $d = 0.33$ for a one-sided one-sample t-test with an $\alpha = \beta = .05$ and a sample of $N = 100$ subjects. As we expected some experimental mortality due to the fact that this experiment was run online, we aimed to collect 10% more than the needed sample, which resulted in a total sample size of 110 subjects. We collected data of $N = 110$ subjects, from which $N = 99$ were complete data sets (48 female, 1 other, $M_{age} = 31.3$, $SD_{age} = 10.0$). Ten subjects were excluded because they had to repeat the instruction check two or more times which resulted in a final sample of $N = 89$ (44 female, 1 other, 16.9% university students). The mean age of the sample was $M_{age} = 31.3$ ($SD_{age} = 10.0$, Range 18–60). All but one subject indicated that they were native English speakers.

6.2 Results

6.2.1 Preregistered analyses

Just as in the first and the second experiment, we hypothesized that the average Attraction Search Score is significantly larger than zero. In order to test this hypothesis, we calculated the individual Attraction Search Scores for all subjects. The mean Attraction Search Score was $M_{ASS} = 0.30$, $t(88) = 7.92$, $p < .001$, Cohen's $d = 0.84$. Therefore, we found evidence for subjects' search behavior being consistent with iCodes's predictions even when the cue-value information was not presented in a matrix.

6.2.2 Exploratory analyses

As a first exploratory analysis, we tested whether we could find an Attraction Search Score larger than zero when looking at the three patterns separately.[15] Each pattern yielded a significantly positive Attraction Search Score, $M_{Pattern1} = 0.18$, $t(88) = 5.47$, $d = 0.58$, $M_{Pattern2} = 0.39$, $t(88) = 6.87$, $d = 0.73$, and $M_{Pattern3} = 0.33$, $t(88) = 6.23$, $d = 0.66$, all $p < .001$. We also calculated the Attraction Search Scores for each article of clothing, which can be found in Figure 4. The heterogeneity between items of clothing seemed to be more pronounced than in Experiment 2 but somewhat less pronounced than in Experiment 1.

We also ran a generalized linear mixed model for Experiment 3. Just as in Experiment 1, the dependent variable was whether subjects searched for Option A in any given trial and the effect-coded predictor was whether Option A was attractive in that trial (Version a; +1) or not (Version b; −1). To account for variation in the data, we added random intercepts for subjects and content scenarios as well as a random slope for *version* for subjects.[16]

The results showed that subjects were on average more likely to search for information on Option A given that this option was attractive, $\beta = 0.76$, $SE = 0.10$, $z = 7.18$, $p < .001$ (see Table B1 and Table B2 for all model estimates). Specifically, the probability of searching information for Option A increased from 18.5% in Version b of the pattern to 51.0% in Version a of the pattern. At the same time, the effect of pattern version varied across subjects systematically, as shown in Figure 6.

To try to explain some of the inter-individual variance in the effect, we added the Helmert-coded *cue pattern* predictor[17] to the model. The effect of *version* was still significantly positive in this model, $\beta = 0.91$, $SE = 0.14$, $z = 6.60$, $p < .001$, indicating that the probability of searching for Option A increased from 14.3% in Version b to 50.8% in Version a. There were also significant effects for both pattern predictors, indicating that subjects were more likely to search for Option A in Pattern 2 compared to Pattern 1, $\beta = 1.36$, $SE = 0.11$, $z = 12.96$, $p < .001$, as well as in Pattern 3 compared to Pattern 1 and 2, $\beta = 0.18$, $SE = 0.05$, $z = 3.81$, $p < .001$. However, there was no significant interaction between the *cue pattern* and the *version* predictors, $ps > .100$.

[15] This analyses included three observations of Version a and three observations of Version b for each subject and each cue-value pattern.

[16] The maximum random model structure did not converge with a random slope for *version* for decision scenarios. Just as in Experiment 2, this random effects structure was achieved by starting with the maximum random structure and then excluding correlations between random effects and random slopes with the least variance successively until the model converged.

[17] Due to the Helmert coding, two predictors were added to the model: the first compared Pattern 3 (+2) against Pattern 1 (−1) and 2 (−1); the second compared Pattern 2 (+1) against Pattern 1 (−1).

6.3 Discussion

The results of Experiment 3 show that the Attraction Search Effect is not restricted to a matrix presentation format but can also be found in a more realistic, less restrictive setting. The effect sizes of the separate cue patterns as well as the absolute Attraction Search Scores are comparable to those of Jekel et al. (2018) in the condition without search costs (see Figure 5), as all three patterns show a medium to large effect. The results plotted in Figure 3 further show that, albeit not restricted to the original cue-value patterns, the effect is more pronounced with the original cue-value patterns, when comparing the results of Experiment 2 with Experiment 3. We do not find the same level of heterogeneity between decision contexts in Experiment 3 compared to the first experiment (see Figure 4). This might be explained by the fact that the decision content is more homogeneous in Experiment 3 compared to Experiment 1 because all decisions were made between articles of clothing. There is also no evidence in the results of Experiment 3 for the same interaction of the cue patterns and the cue pattern version that was found in Experiment 1. The absent interaction is probably due to two reasons: first, the original effect sizes in Jekel et al. (2018) of the cue patterns used in Experiment 3 were more homogenous from the start when compared to the cue patterns from Experiment 1. Second, the interaction between subjective importance of cues and option attractiveness was reduced in Experiment 3 as the ordering of the cues' importance was given at the start of the experiment.

7 General discussion

The Attraction Search Effect is the core prediction by iCodes that states that information search is influenced not only by the validity of the information but also by the attractiveness of the options. Jekel et al. (2018) provided first evidence for this prediction in three experiments that all shared the same task characteristics and the same semantic content. The goal of the current project was to test the range of applicability of iCodes's search predictions. For this purpose, we ran three conceptual replications of the original studies that varied aspects that were kept constant in the original experiments. In the first experiment, we showed that the Attraction Search Effect is not restricted to the probabilistic-inference tasks in Jekel et al.'s (2018) experiments but also emerges in preferential decision tasks in six every-day content domains. The results of the second experiment, which was preregistered, illustrate that the Attraction Search Effect generalizes to a wider range of different semantic contexts and further show that the Attraction Search Effect also emerges without specifically designed and diagnostic cue-value patterns, albeit with a somewhat reduced effect size. In the last experiment, also preregistered, we found evidence that the Attraction Search Effect is also present when one moves away from the classic matrix format of information presentation to a more realistic simulated online-shop setting. Thus, we found evidence for iCodes's information-search prediction in three experiments with in total 627 subjects. These results show that the influence of the already available information on information-search direction is a robust phenomenon that can be found in different variants of the classic multi-attribute decision task. They further strengthen iCodes as a general theory of decision making and information search.

7.1 Limitations and future directions

The results of Experiment 2 show that there are boundary conditions for the generalizability of the Attraction Search Effect. As the second experiment was the only experiment that did not use the cue-value patterns from Jekel et al. (2018) and did not restrict information search to one piece of information, it is likely that the reduced effect size in Experiment 2 was at least partially caused by the change in the experimental setup. The change from specifically designed, diagnostic cue-value patterns to randomized cue-value patterns naturally weakens the effect of the experimental manipulation, as the reduced experimental control due to the randomization of cue values may have increased the noise in the data. The second aspect that was different in Experiment 2 compared to the two other experiments was that search was less restrictive. The original results by Jekel et al. (2018) showed that costly or restricted search is relevant for the strength of the Attraction Search Effect. It is possible that the restriction of search, that varies from trial to trial, we used to implement search costs was not strong enough to elicit a reliable Attraction Search Effect for many subjects who instead opted for a heuristic search strategy. This assumption is supported by the fact that subjects that showed no Attraction Search Effect tended to search for more information and did so faster than subjects that did show the Attraction Search Effect in this experiment, just like subjects in the condition without search costs in Jekel et al. (2018). In fact, individual Attraction Search Scores tended to be lower for subjects that used cue-wise search strategies more often and higher for subjects whose search behavior could not be classified as belonging to one search strategy.

The results of Experiment 2 show that we observed larger interindividual heterogeneity in the Attraction Search Effect than in Experiments 1 and 3 in this paper (see Figure 3). This larger heterogeneity in Experiment 2 was also revealed by the mixed model analyses of all three experiments. The fact that the most variance in individual Attraction Search Effects was found in Experiment 2 hints that the diagnostic cue-value patterns as well as the restricted information search are relevant for the homogeneity and strength of the effect. Future research should tease apart the effects underlying the heterogeneity of the Attraction Search Effect.

The variability of individual Attraction Search Effects in Experiment 2 also points to hidden moderators determining the individual strength of the effect. Jekel et al. (2018) already identified search costs as a moderator of the Attraction Search Effect and the results of Experiment 2 corroborate this finding. A still unanswered question is what happens to the information-search process when information-search costs are introduced. One explanation for the effect of search costs might be that costs increase the deliberation about the search decision (Jekel et al., 2018). This assumption is corroborated by the fact that subjects with a higher Attraction Search Score tend to take slightly longer to search for the first piece of information. A promising avenue for future research is to investigate the role of deliberation in the Attraction Search Effect more closely, for example by employing dual-task (Schulze & Newell, 2016) or time-pressure manipulations (Rieskamp & Hoffrage, 2008; Payne et al., 1988). Further, the emergence of the Attraction Search Effect might be moderated by different individual characteristics. One may assume, for example, that subjects differ in their tendency to focus on the more attractive option (Mather & Carstensen, 2005; Noguchi et al., 2006). When investigating potential moderators of the effect, one should keep in mind that using the original cue-value patterns decreases heterogeneity of the Attraction Search Effect and thus might mask interinidvidual differences.

While finding substantial interindividual differences in the Attraction Search Effect, we find only a little evidence for differences in Attraction Search Effect between content scenarios. Only in Experiment 1 do we find support for differences between decision contexts from the mixed model analyses. This might be due to the fact that in that experiment only the order of subjective importance for the cues was implied rather than explicitly stated (Experiment 3) or inferred from subjects' behavior (Experiment 2). This explanation is further supported by the fact that the same decision scenarios that differed in effect size in Experiment 1 were also included in Experiment 2 and did not show the same variability in that experiment. The findings with regard to decision contexts emphasize the role of cues' importance in the information-search process and, thus, reveals an important variable to control in future investigations of the Attraction Search Effect.

When comparing our results to those from Jekel et al. (2018), we find that the overall Attraction Search Score results from Experiments 1 and 3 are similar to those of the experiments with restricted and costly information search by Jekel et al. (2018), whereas the results from Experiment 2 are comparable to Jekel et al.'s experiment without information search costs (see Figure 5). The effect sizes in our three experiments are considerably reduced compared to the original results, but they are still medium (Experiment 2) to large (Experiment 1 and 3). Next to reducing the level of experimental control in our replications, this decrease is probably also due to the reduced number of trials in our studies, which reduces the reliability of the estimation per individual. Nonetheless, the fact that we are still able to find the Attraction Search Effect with fewer trials opens up the possibility to investigate even more diverse contexts.

One of iCodes' advantages is that it is a fully formalized model that gives process descriptions of a well-documented phenomenon of information search (Doherty et al., 1979; Mynatt et al., 1993; Hart et al., 2009). The formalization of iCodes allows researchers to determine the fit of the observed behavior with model predictions and to compare this fit with the search predictions of other models for information search (Jekel et al., 2018). One prerequisite for fitting iCodes, however, is knowing the exact cue validities, as they heavily influence iCodes predictions. In case of preferential tasks, the importance of cues is difficult to determine due to the subjective nature of the relative importance of the cues. Further, we do not know the relationship between ratings of importance and perceptions of cue validities. In the current experiments, we opted to test iCodes's qualitative predictions for information search only. In order to fit iCodes to search behavior in preferential tasks, one might utilize methods such as conjoint analysis (as, for example, done in Meißner et al., 2015) in order to deduce the individual importance weights.

In this project, we varied the semantic content, the cue-value patterns, and the way of information was presented to test whether the Attraction Search Effect generalizes to various decision settings. However, there are still multiple aspects of the decision situation that have been kept constant between the experiments in this project and the experiments by Jekel et al. (2018). A next step might be to change the way information is presented more radically, for example by randomizing the position of the information on the screen between trials, as has been done for instance in Söllner et al. (2013), so that subjects can not memorize the positions on screen. In addition, it might be interesting to refrain from using variants of the classic decision board altogether by utilizing a procedure in which subjects can naturally search for information by asking questions (Huber et al., 2011). Another characteristic all studies shared was that information search was tracked in a mouselab-type setting via recording mouse clicks on a computer screen. As using the mouselab setup for process tracing might influence information search (Glöckner & Betsch, 2008; Lohse & Johnson, 1996), a fruitful avenue for future research might be to investigate information search with other process-tracing measures such as eye-tracking. Utilizing eye-tracking as a process-tracing method for information search would further allow one to observe information-search behavior in naturalistic settings, such as an actual online shop.

With showing that the Attraction Search Effect appears in diverse settings, we take a step closer to connecting iCodes's predictions to the already existing literature on biased information search. Selective exposure, pseudo-diagnostic search, and leader-focused search have all been investigated in various semantic settings and paradigms (Mynatt et al., 1993; Fraser-Mackenzie & Dror, 2009; Carlson & Guha, 2011). In this project, we could show that the Attraction Search Effect also generalizes to diverse contextual settings. In future research, the iCodes model could be extended in such a way that it can be applied to data from different research paradigms for biased information search. Doing so would allow a bridge to prior research and extend the applicability of iCodes. It would also allow researchers to test which parameters in the iCodes model are affected by manipulations that have been known to influence biased information search (see Hart et al., 2009, for an overview of potential moderators of selective exposure).

7.2 Conclusion

We showed that the Attraction Search Effect, an important prediction of the new iCodes model, is a robust finding that is not restricted to specific decision task settings. The results of the three experiments further highlight that the already available information about choice options is highly relevant for information search and that the direction of information search is not necessarily subject to strict rules but rather is influenced by coherence as well.

References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1–48, https://doi.org/10.18637/jss.v067.i01.

Bettman, J. R. & Kakkar, P. (1977). Effects of information presentation format on consumer information acquisition strategies. *Journal of Consumer Research*, *3*(4), 233–240, https://doi.org/10.1086/208672.

Bredenkamp, J. (1980). *Theorie und Planung Psychologischer Experimente*. Heidelberg: Steinkopff-Verlag.

Bröder, A. (2000). Assessing the empirical validity of the "take-the-best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1332–1346, https://doi.org/10.1037/0278-7393.26.5.1332.

Bröder, A. (2003). Decision making with the "adaptive toolbox": Influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(4), 611–625, https://doi.org/10.1037/0278-7393.29.4.611.

Böckenholt, U. & Hynan, L. S. (2006). Caveats on a process-tracing measure and a remedy. *Journal of Behavioral Decision Making*, *7*(2), 103–117, https://doi.org/10.1002/bdm.3960070203.

Carlson, K. A. & Guha, A. (2011). Leader-focused search: The impact of an emerging preference on information search. *Organizational Behavior and Human Decision Processes*, *115*(1), 133–141, https://doi.org/10.1016/j.obhdp.2010.12.002.

Doherty, M. E., Mynatt, C. R., Tweney, R. D., & Schiavo, M. D. (1979). Pseudodiagnosticity. *Acta Psychologica*, *43*(2), 111–121, https://doi.org/10.1016/0001-6918(79)90017-9.

Ettlin, F., Bröder, A., & Henninger, M. (2015). A new task format for investigating information search and organization in multiattribute decisions. *Behavior Research Methods*, *47*(2), 506–518, https://doi.org/10.3758/s13428-014-0482-y.

Evans, J. S. B. T., Venn, S., & Feeney, A. (2002). Implicit and explicit processes in a hypothesis testing task. *British Journal of Psychology*, *93*(1), 31–46, https://doi.org/10.1348/000712602162436.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191, https://doi.org/10.3758/BF03193146.

Fischer, P. & Greitemeyer, T. (2010). A New Look at Selective-Exposure Effects: An Integrative Model. *Current Directions in Psychological Science*, *19*(6), 384–389, https://doi.org/10.1177/0963721410391246.

Fischer, P., Lea, S., Kastenmüller, A., Greitemeyer, T., Fischer, J., & Frey, D. (2011). The process of selective exposure: Why confirmatory information search weakens over time. *Organizational Behavior and Human Decision Processes*, *114*(1), 37–48, https://doi.org/10.1016/j.obhdp.2010.09.001.

Fraser-Mackenzie, P. A. F. & Dror, I. E. (2009). Selective information sampling: Cognitive coherence in evaluation of a novel item. *Judgment and Decision Making*, *4*(4), 307–316.

Frey, D. (1986). Recent Research on Selective Exposure to Information. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology*, volume 19 (pp. 41–80). Academic Press.

Gigerenzer, G., Dieckmann, A., & Gaissmaier, W. (2014). Efficient cognition through limited search. In P. M. Todd, G. Gigerenzer, & T. A. R. Group (Eds.), *Ecological Rationality: Intelligence in the World*. Cary: Oxford University Press.

Gigerenzer, G. & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669, https://doi.org/10.1037/0033-295X.103.4.650.

Gigerenzer, G. & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. In *Simple heuristics that make us smart*, Evolution and cognition. (pp. 3–34). New York: Oxford University Press.

Glöckner, A. & Betsch, T. (2008). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(5), 1055–1075, https://doi.org/10.1037/0278-7393.34.5.1055.

Glöckner, A. & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologica*, *139*(3), 532–542, https://doi.org/10.1016/j.actpsy.2012.01.009.

Glöckner, A., Betsch, T., & Schindler, N. (2010). Coherence shifts in probabilistic inference tasks. *Journal of Behavioral Decision Making*, *23*(5), 439–462, https://doi.org/10.1002/bdm.668.

Glöckner, A., Heinen, T., Johnson, J. G., & Raab, M. (2012). Network approaches for expert decisions in sports. *Human Movement Science*, *31*(2), 318–333, https://doi.org/10.1016/j.humov.2010.11.002.

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666, https://doi.org/10.1016/j.cognition.2014.08.017.

Glöckner, A. & Hodges, S. D. (2010). Parallel constraint satisfaction in memory-based decisions. *Experimental Psychology*, *58*(3), 180–195, https://doi.org/10.1027/1618-3169/a000084.

Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., & Merrill, L. (2009). Feeling validated versus being correct: A meta-analysis of selective exposure to information. *Psychological Bulletin*, *135*(4), 555–588, https://doi.org/10.1037/a0015701.

Harte, J. M. & Koele, P. (2001). Modelling and describing human judgement processes: The multiattribute evaluation case. *Thinking & Reasoning*, *7*(1), 29–49, https://doi.org/10.1080/13546780042000028.

Hausmann, D. & Läge, D. (2008). Sequential evidence accumulation in decision making: The individual desired level of confidence can explain the extent of information acquisition. *Judgment and Decision Making*, *3*(3), 229–243.

Henninger, F., Shevchenko, Y., Mertens, U. K., & Hilbig, B. E. (in press). lab.js: A free, open, online study builder. *Behavior Research Methods*, https://doi.org/10.5281/zenodo.597045.

Huber, O., Huber, O. W., & Schulte-Mecklenbeck, M. (2011). Determining the information that participants need: Methods of active information search. In M. Schulte-Mecklenbeck, A. Kühberger, & R. Ranyard (Eds.), *A Handbook of Process Tracing Methods for Decision Research: A Critical Review and User's Guide* (pp. 65–85). New York: Psychology Press.

Jekel, M., Glöckner, A., & Bröder, A. (2018). A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect. *Psychological Review*, *125*(5), 744–768, https://doi.org/10.1037/rev0000107.

Johnson, E. J., Payne, J. W., Bettman, J. R., & Schkade, D. A. (1989). *Monitoring information processing and decisions: The mouselab system*. Technical report, Duke University, Durham, NC, Center For Decision Studies.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*(13), 1–26, https://doi.org/10.18637/jss.v082.i13.

Lee, M. D. & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review*, *11*(2), 343–352, https://doi.org/10.3758/BF03196581.

Lohse, G. L. & Johnson, E. J. (1996). A comparison of two process tracing methods for choice tasks. *Organizational Behavior and Human Decision Processes*, *68*(1), 28–43, https://doi.org/10.1006/obhd.1996.0087.

Makel, M. C., Plucker, J. A., & Hegarty, B. (2012). Replications in psychology research: How often do they really occur? *Perspectives on Psychological Science*, *7*(6), 537–542, https://doi.org/10.1177/1745691612460688.

Marewski, J. N. (2010). On the theoretical precision and strategy selection problem of a single-strategy approach: A comment on Glöckner, Betsch, and Schindler (2010). *Journal of Behavioral Decision Making*, *23*(5), 463–467, https://doi.org/10.1002/bdm.680.

Mather, M. & Carstensen, L. L. (2005). Aging and motivated cognition: the positivity effect in attention and memory. *Trends in Cognitive Sciences*, *9*(10), 496–502, https://doi.org/10.1016/j.tics.2005.08.005.

Meißner, M., Musalem, A., & Huber, J. (2015). Eye tracking reveals processes that enable conjoint choices to become increasingly efficient with practice. *Journal of Marketing Research*, *53*(1), 1–17, https://doi.org/10.1509/jmr.13.0467.

Mynatt, C. R., Doherty, M. E., & Dragan, W. (1993). Information relevance, working memory, and the consideration of alternatives. *The Quarterly Journal of Experimental Psychology Section A*, *46*(4), 759–778, https://doi.org/10.1080/14640749308401038.

Newell, B. R., Weston, N. J., & Shanks, D. R. (2003). Empirical tests of a fast-and-frugal heuristic: Not everyone "takes-the-best". *Organizational Behavior and Human Decision Processes*, *91*(1), 82–96, https://doi.org/10.1016/S0749-5978(02)00525-3.

Noguchi, K., Gohm, C. L., & Dalsky, D. J. (2006). Cognitive tendencies of focusing on positive and negative information. *Journal of Research in Personality*, *40*(6), 891–910, https://doi.org/10.1016/j.jrp.2005.09.008.

Palan, S. & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22–27, https://doi.org/10.1016/j.jbef.2017.12.004.

Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance*, *16*(2), 366–387, https://doi.org/10.1016/0030-5073(76)90022-2.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552, https://doi.org/10.1037/0278-7393.14.3.534.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge: University Press.

Questback (2016). Unipark EFS Survey (Version 10.9).

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

Rieskamp, J. & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276, https://doi.org/10.1016/j.actpsy.2007.05.004.

Scharf, S., Wiegelmann, M., & Bröder, A. (2017). Generalizability of the attraction search effect. (Preregistration.) https://osf.io/j7vg4/.

Scharf, S., Wiegelmann, M., & Bröder, A. (2018). Generalizability of the attraction search effect. (Preregistration). https://osf.io/nfruq/.

Schkade, D. A. & Kleinmuntz, D. N. (1994). Information displays and choice processes: Differential effects of organization, form, and sequence. *Organizational Behavior and Human Decision Processes*, *57*(3), 319–337, https://doi.org/10.1006/obhd.1994.1018.

Schulze, C. & Newell, B. R. (2016). Taking the easy way out? Increasing implementation effort reduces probability maximizing under cognitive load. *Memory & Cognition*, *44*(5), 806–818, https://doi.org/10.3758/s13421-016-0595-x.

Shevchenko, Y. (2019). Multi-attribute task builder. *Journal of Open Source Software*, *38*(4), 1409, https://doi.org/10.21105/joss.01409.

Stark, C. E. L. & McClelland, J. L. (2000). Repetition priming of words, pseudowords, and nonwords. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(4), 945–972, https://doi.org/10.1037/0278-7393.26.4.945.

Söllner, A., Bröder, A., & Hilbig, B. E. (2013). Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making? *Judgment and Decision Making*, *8*(3), 278–298.

Wells, G. L. & Windschitl, P. D. (1999). Stimulus Sampling and Social Psychological Experimentation. *Personality and Social Psychology Bulletin*, *25*(9), 1115–1125, https://doi.org/10.1177/01461672992512005.

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. New York: Springer-Verlag.

Wilson, T. D., Wheatley, T., Meyers, J. M., Gilbert, D. T., & Axsom, D. (2000). Focalism: A source of durability bias in affective forecasting. *Journal of Personality and Social Psychology*, *78*(5), 821–836, https://doi.org/10.1037/0022-3514.78.5.821.

Appendix A: Results for importance ratings in Experiment 1

These are the results of the cue ratings made by subjects in Experiment 1. Subjects had to answer the question "How important were these dimensions for you when deciding between (decision scenario)?".

Table A1: Mean importance ratings and respective standard deviations of scenarios' cues in Experiment 1.

City Size Scenario		Hair Salon Scenario	
Cue	M_{Rating} (SD)	Cue	M_{Rating} (SD)
State Capital	57.47 (32.66)	Competency	85.16 (22.04)
International Airport	68.05 (29.81)	Price	58.02 (26.02)
University	47.36 (28.24)	Proximity to Home	37.59 (26.62)
Opera	36.99 (29.95)	Scheduling Appointments	36.31 (26.68)
Hotel Scenario		**Job Scenario**	
Cue	M_{Rating} (SD)	Cue	M_{Rating} (SD)
Proximity to Beach	59.07 (29.51)	Pay	72.41 (23.32)
Price	64.70 (24.84)	Working Conditions	73.52 (27.33)
Proximity to City Center	37.67 (26.01)	Colleagues	64.64 (28.43)
Cleanliness	76.33 (27.15)	Proximity to Home	44.95 (27.35)
Pizza Service Scenario		**Weather Forecast Scenario**	
Cue	M_{Rating} (SD)	Cue	M_{Rating} (SD)
Quality	89.16 (18.21)	German Weather Service	82.68 (24.89)
Price	55.12 (26.32)	"ZDF" Weather Forecast	63.22 (30.12)
Timeliness	47.25 (28.04)	"BILD" Weather Forecast	23.69 (24.09)
Friendliness	33.33 (27.04)	Horoscope	5.17 (12.54)

Note. Ratings were made on a scale from 0 to 100; the displayed order of the cues in the tables represents the displayed order, and therefore the assumed ranking, of the cues in the experiment.

Appendix B: Results of mixed logistic regressions of all three experiments

Table B1. Variances and correlations of random effects in mixed logistic regressions for Experiment 1–3.

	Model 1		Model 2	
Random Effects	Variance	Correlation	Variance	Correlation
Experiment 1				
Subject				
Intercept	0.04		0.16	
Pattern Version	0.06		0.18	
Intercept, Pattern Version		−.42		−.35
Decision Scenarios				
Intercept	0.07		0.08	
Pattern Version	0.05		0.07	
Intercept, Pattern Version		.00		−.02
Experiment 2				
Subjects				
Intercept	3.12		1.96	
Valence of First Search	0.60		0.59	
Intercept, Valence of First Search		0.40		0.26
Decision Scenarios				
Intercept	0.01		0.01	
Experiment 3				
Subjects				
Intercept	0.11		0.31	
Pattern Version	0.63		1.11	
Intercept, Pattern Version		0.67		0.71
Shop Item				
Intercept	0.05		0.07	

Note. Model 1 represents the mixed logistic regression with only one predictor: *pattern version* in Experiment 1 and 3 and the valence of the first searched-for cue value in Experiment 2. Model 2 includes the *cue pattern* predictor for Experiment 1 and 3 and the *strategy count* predictor for Experiment 2.

Table B2. Fixed effects estimates of mixed logistic regressions for Experiment 1–3.

	Model 1				Model 2			
Fixed Effects	*B*	SE	*z*	*p*	*B*	SE	*z*	*p*
Experiment 1								
Intercept	−0.53	0.12	−4.40	<.001	−0.64	0.14	−4.67	<.001
Version a	0.75	0.11	6.77	<.001	0.88	0.13	6.84	<.001
Pattern 1 vs. Pattern 2					−0.80	0.07	−10.75	<.001
Patterns 1 & 2 vs. Pattern 3					0.02	0.04	0.58	.563
Version a * Pattern 1 vs. Pattern 2					0.16	0.07	2.14	.032
Version a * Patterns 1 & 2 vs. Pattern 3					0.15	0.04	3.73	<.001
Experiment 2								
Intercept	−2.29	0.15	−15.42	<.001	−2.32	0.13	−17.52	<.001
Valence positive	0.38	0.11	3.58	<.001	0.38	0.11	3.63	<.001
Strategy Count					−0.41	0.04	−9.99	<.001
Valence positive * Strategy Count					−0.09	0.03	−2.71	.007
Experiment 3								
Intercept	−0.72	0.09	−8.09	<.001	−0.88	0.12	−7.38	<.001
Version a	0.76	0.11	7.18	<.001	0.91	0.14	6.60	<.001
Pattern 1 vs. Pattern 2					1.36	0.11	12.96	<.001
Patterns 1 & 2 vs. Pattern 3					0.18	0.05	3.81	<.001
Version a * Pattern 1 vs. Pattern 2					0.17	0.10	1.64	.100
Version a * Patterns 1 & 2 vs. Pattern 3					−0.01	0.05	−0.22	.828

Note. Predictors *valence* and *version* were both effect coded in all analyses, such that Version a/positive valence was coded with +1 and Version b/negative valence with −1. The predictor *pattern* in Experiment 1 and 3 was Helmert-coded, always comparing the cue pattern with the strongest effect in Jekel et al. (2018) with the remaining cue patterns. Thus, Pattern 3 (+2) was compared to Patterns 1 and 2 (both −1) and Pattern 2 (+1) was compared with Pattern 1 (−1) in both experiments. The predictor *strategy count* was mean centered across subjects.

Appendix C: The effect of (mis-)match in importance ratings on the attraction search effect

We ran a generalized linear mixed model with the data from Experiment 1, including the individual (rank) correlations of the intended ordering of the cues and the ordering of the cues following subjects' ratings for each scenario. Thus, a high, positive correlation represents very similar orderings, whereas a zero correlation represents no association of the intended and the rated cue ordering. Just as with the other mixed logistic regressions, the dependent variable was whether subjects searched for Option A in any given trial and the effect-coded predictor whether Option A was attractive in this trial (Version a; +1) or not (Version b; −1). To account for systematic variation in the data, we added random intercepts for subjects and content scenarios as well as a random slopes for *version* for both subjects and content scenarios. We additionally included the (as described above) Helmert-coded *cue pattern* predictor as well as the individual rank correlations in the model.

The effect of interest here is the interaction of *version* and *rank correlation*, $\beta = 0.26$, $SE = 0.14$, $z = 1.91$, $p = .056$. Although the interaction is not significant, the predicted probabilities for searching for Option A depict the expected pattern: The probability to search for Option A increases from 21.0% in trials with Version b to 42.3% in trials with Version a, when the correlation of subjective cue order and intended cue order is −1. When the subjective cue order and intended cue order are not correlated at all, the probability to search for Option A increases from 18.8% in trials with Version b to 52.1% in trials with Version a. Finally, when the cue orderings are perfectly (positively) correlated, the probability of searching for Option A in Version b is 16.9% and in Version a 61.8%. Thus, the effect of version on search behavior increases with an increasing correlation between the intended and the rated cue ordering. The remaining results from this analyses can be found in Tables C1 and C2. One thing to note is that compared to the analyses of Model 2 from Experiment 1 (see Tables C1 and C2), the variance of the Decision Scenarios random slope slightly increased when including the rank correlation predictor (from 0.07 in Model 2 of Experiment 1 to 0.08 in the Model with rank correlations as predictor). Thus, it is not entirely clear whether including the rank correlations actually explained variation in the effect of pattern version between Decision Scenarios.

Table C1. Variances and correlations of random effects in mixed logistic regressions for Experiment 1 including rank correlations.

Random Effects	Variance	Correlation
Subjects		
Intercept	0.16	
Pattern Version	0.15	−.23
Scenarios		
Intercept	0.04	
Pattern Version	0.08	−.10

Table C2. Fixed effects estimates of mixed logistic regressions for Experiment 1 including rank correlations.

Fixed Effects	Estimate	SE	*z*	*p*
Intercept	−0.69	0.13	−5.21	<.001
Version a	0.77	0.15	5.05	<.001
Pattern 1 vs. Pattern 2	−0.07	0.10	−0.73	.465
Patterns 1 & 2 vs. Pattern 3	0.01	0.06	0.16	.870
Rank Correlations	0.13	0.14	0.92	.359
Version a * Pattern 1 vs. Pattern 2	0.26	0.10	2.58	.010
Version a * Patterns 1 & 2 vs. Pattern 3	0.12	0.06	2.09	.037
Version a * Rank Correlation	0.26	0.14	1.91	.056
Pattern 1 vs. Pattern 2 * Rank Correlation	−1.42	0.15	−9.76	<.001
Patterns 1 & 2 vs. Pattern 3 * Rank Correlation	0.02	0.08	0.28	.783
Version a * Pattern 1 vs. Pattern 2 * Rank Correlation	−0.20	0.15	−1.40	.162
Version a * Patterns 1 & 2 vs. Pattern 3 * Rank Correlation	0.01	0.08	0.18	.860

Note. Predictor *version* was effect coded, such that Version a was coded with +1 and Version b with −1. The predictor *pattern* was Helmert-coded, comparing the cue pattern with the strongest effect in Jekel et al. (2018) with the remaining cue patterns. Thus, Pattern 3 (+2) was compared to Patterns 1 and 2 (both −1) and Pattern 2 (+1) was compared with Pattern 1 (−1) in both experiments.

Testing an extension of the iCodes model to account for situation, person, and task specific variation in the attraction search effect

Sophie E. Scharf
University of Mannheim

Marc Jekel, Andreas Glöckner
University of Cologne

Author Note

This research was supported by a grant of the German Science Foundation (Deutsche Forschungsgemeinschaft, DFG) awarded to Andreas Glöckner (GL 632/5-1) and Arndt Bröder (BR 2130/13-1). Part of the data and ideas were presented at SPUDM (Amsterdam, Netherlands, 2019), and ESCOP (Tenerife, Spain, 2019). The article hast not been made available on any online depository or website previously. We thank Arndt Bröder for detailed feedback on the research idea and helpful comments on an earlier draft of this manuscript. Correspondence concerning this article should be addressed to Sophie E. Scharf, Department of Psychology, School of Social Sciences, University of Mannheim, 68131 Mannheim, Germany. E-mail: sophie.scharf@gess.uni-mannheim.de

Abstract

Previous research has shown that the tendency to search information for an option increases with option attractiveness. This attraction search effect (ASE) can be explained by the *integrated coherence-based decision and search* (iCodes) model. In a pre-registered study (N = 202), we investigated whether the ASE is moderated by explicit awareness of the attractiveness of an option. Persons made repeated choices between options in a task in which information was only partially accessible in a first stage. More information could be actively searched in a second stage. In the experimental condition, participants rated options' attractiveness after the first stage, while the control group did not. The manipulation increased the magnitude of the ASE as hypothesized and led to increased search for the emerging favored option. An extended iCodes model that includes a mixture parameter γ could account for the moderating situational effect. The extended model also captured reliable interindividual differences concerning the ASE and predicted the magnitude of the effect for different cue patterns. The results of this project provide further evidence for the validity of iCodes which not only predicts the effect of attractiveness ratings but also maps the effect on the theoretically adequate parameter. Implications for further theory development and theory integration are discussed.

Keywords: Information Search; Coherence; Parallel Constraint Satisfaction Network Model; Attraction Search Effect; Parameter Validation

Testing an extension of the iCodes model to account for situation, person, and task specific variation in the attraction search effect

Many prominent models in decision making predict that information search follows a fixed search rule. In a decision between two products individuals might, for example, apply a lexicographic strategy (e.g., Payne et al., 1988; see also take-the-best heuristic, Gigerenzer & Goldstein, 1996), and search information along attributes or cues starting with the subjectively most important or valid one. In these classic models, search is driven by decision strategies only and should be independent of factors such as the content of the information and the emerging attractiveness of an option. Yet, recent research has shown that individuals tend to search information for options that appear to be more attractive according to previously searched information (Jekel et al., 2018). This attraction search effect (ASE) has been shown to be robust across various conditions (Jekel et al., 2018), observable for various kinds of decision tasks (e.g., probabilistic inferences, Jekel et al., 2018; preferential choice, Scharf et al., 2019), and of considerable magnitude (average d = 1.10; Jekel et al., 2018). The *integrated coherence-based decision and search* model (iCodes; Jekel et al., 2018) can account for influences of options' attractiveness on information search as well as various other findings (e.g., Glöckner et al., 2014; Söllner et al., 2014). ICodes is based on a neural network (details below) and predicts that both, more valid information and information for the more attractive option, are more likely to be searched for.

Previous studies showed substantial variations in the magnitude of the ASE, i.e. it was stronger when search was limited or costly and smaller for situations with unlimited and free search (Jekel et al., 2018). Participants also reliably showed differences in the strength of the ASE over repeated trials, indicating some degree of interindividual differences (Jekel et al., 2018; Scharf et al., 2019).

In the current paper, we test whether the strength of the ASE increases with participants' awareness of option attractiveness. We manipulate this awareness between-subjects by asking participants to rate the attractiveness of the options before active information search while the control condition did not give a rating. Based on iCodes, highlighting the attractiveness of options should lead to an increased weighting of option-attractiveness influences on search and, thus, to an increased ASE.

To account for shifts in the relative influence of effects of option attractiveness as compared to cue validity, we extend iCodes by including a mixture parameter γ. We examine whether accounting for situational and interindividual variance in search by including γ in iCodes improves the model's ability to predict search behavior.

Coherence-Based Decision Making and Search

Coherence-based models for decision making assume that individuals strive for coherent interpretations of the available information (Glöckner & Betsch, 2008; Holyoak & Simon, 1999; Thagard & Millgram, 1997; Thagard, 1989, see also, Montgomery, 1989; Pennington & Hastie, 1986; Svenson, 1992). In this process, initial advantages of one option over the others are accentuated and the emerging favored option is chosen. In contrast to classic models of decision making such as the adaptive decision maker (Payne et al., 1988) or the adaptive toolbox (Gigerenzer, 2001; Gigerenzer & Todd, 1999), no serial-stepwise processing of information is assumed. Information integration is modelled using neural networks that have been adapted from perception (McClelland & Rumelhart, 1981) and are commonly used in many areas of psychology (for overviews, see McClelland et al., 2014; Read et al., 1997).

With iCodes, coherence-based decision making has been extended to not only simulate choice but also active information search (Jekel et al., 2018; Scharf et al., 2019). ICodes generalizes the coherence principle to information search by assuming that the attractiveness of an option and the validity of a cue jointly influence which information is searched next. The relative impact of attractiveness during information search is modulated by the parameter γ in iCodes (see Figure 1). γ represents the relative influence of attractiveness in the information-search process. A $\gamma = 0.5$ would indicate that the influences of option attractiveness and cue validity are equally strong during information search. In the original specification of iCodes (Jekel et al., 2018), $\gamma = 0.09$ was used as fixed parameter, indicating that the impact of information validity is ten times higher than option attractiveness on search. Importantly, according to iCodes, the magnitude of the attraction search effect increases with mixture parameter γ, since the ASE directly results from the influence of option attractiveness.

Potential Moderators of the Attraction Search Effect (ASE)

From a theoretical perspective, it is plausible to assume that the relative importance of options' attractiveness and cue validity, and consequently also the ASE, are influenced by situational and personal factors. Persons might differ in their general tendency to focus on validities or rather on option attractiveness. Context factors such as time pressure or distraction might also reduce an individual's tendencies to form attractiveness impressions, which are required for attraction effects to appear.

Previous studies showed that search costs and restricted search lead to larger ASE as compared to situations of free search (Jekel et al., 2018; Scharf et al., 2019). Arguably, both manipulations entail more situational pressure to form option-attractiveness impressions early in the search process than free search. Adaptations of the mixture parameter γ iCodes might be required to account for these differences. In the current study, we aim to test this assumption by asking half of the participants to give option-attractiveness ratings before search.

The inclusion of attractiveness ratings in Fraser-Mackenzie and Dror (2009) increased selective-exposure effects, in that information that supported the favored option was more likely searched.[1] We expect the inclusion of attractiveness ratings to increase the strength of the ASE as well as the size of γ in our experiment by increasing the awareness of options' attractiveness. Further, we expect the effect of the attractiveness-rating manipulation to depend on the coherence of the already available evidence in a trial and, therefore, systematically differ between different search trials. That is, more coherent decision situations (e.g., almost all information speaks for an

[1] Note, that the ASE and selective exposure differ conceptually, since the latter requires a priori information concerning whether a piece of information will support the currently favored option, whereas ASE does not.

option) lead to a clearer preference for one of the options and are, therefore, predicted to also lead to a stronger impact of attractiveness during search.

Methods

This experiment was preregistered with a pre-data report (https://osf.io/qrwmz/). The materials, instructions and analyses can be found at https://osf.io/4khmq/?view_only=22284fc9536b4590b918585f4627f365.

Hypotheses

We assume that our experimental manipulation affects search behavior by increasing the weight of the attractiveness influence in the search process. We, therefore, tested the following hypotheses:

1. The Attraction Search Score is higher in the experimental as compared to the control group.
2. In an a priori simulation study, we predicted the first opened cue value and its respective search probability for all 16 cue-value patterns (eight cue patterns in two versions) in both experimental conditions.[2] We, then, ranked the predicted search probabilities for these 16 cue-value patterns, separately for each condition.

[2] In the simulation, we tested how well the mixture parameter γ representing the relative influence of attractiveness on information search can be implemented in the model. This simulation revealed that changing γ influenced the search predictions for the single cue-value patterns to a varying extent. To test whether we can predict (cue) pattern-level effects in our experimental data, we simulated the conditions with and without attractiveness ratings with fixed parameters $P = 1.9$ and $\lambda = 18.9$. We assumed two extreme γ values for both conditions: In the condition with attractiveness ratings, we assumed that the attractiveness influence on information search would be just as strong as the validity influence ($\gamma = 0.5$) while in the condition without attractiveness ratings the validity influence would be 20 times stronger than the attractiveness influence ($\gamma = 0.05$). As we had not yet fitted γ to experimental data, these values were estimates based on the good fit of $\gamma = 0.09$ in Jekel et al. (2018)'s studies. The simulation and its results are accessible at https://osf.io/4khmq/?view_only=22284fc9536b4590b918585f4627f365, further details can be found in the online supplement.

We expect a positive correlation of these predicted rankings with search probability rankings based on the observed information search. The observed rankings are derived from the relative search frequencies for the cue values that have been predicted to be opened first based on the a priori model simulation.

3. The individually fitted γ parameters are on average larger in the experimental group than in the control group. Larger γ values indicate a relatively stronger attractiveness influence on information search. We will also explore whether fitting individual γ parameters improves model fit compared to fitting one γ parameter for all participants.

Participants and Design

Data were collected via the Hagen Decision Lab participant pool. We expected an effect size of Cohen's $d = 0.50$ for the effect of attractiveness ratings on the Attraction Search Score, based on an exploratory comparison of previous studies. Targeting at an $\alpha = \beta = .05$, the required sample to find a medium-sized effect with a one-sided, two-sample t test with equal group sizes is $N = 176$. After ending data collection, we collected complete data sets from $N_{final} = 202$ (125 female, 7 unclassified, $M_{age} = 35.73$, $range : 18 - 78$) with $N_{WithRating} = 87$ in the group with attractiveness ratings and $N_{NoRating} = 115$ in the control group.[3] With this sample size, the achieved power to find a Cohen's $d = 0.50$ is $1 - \beta = .969$.

We manipulated between-subjects whether participants had to rate vs. not rate the attractiveness of options before search. Participants were randomly assigned to one of the two conditions. The attractiveness of options was manipulated within-subjects via the cue-value pattern (Version A vs. Version B). Cue-value patterns in each condition were repeated 8 times in each version, resulting in a total of 128 trials per participant. We further counterbalanced on which side Option A was presented (left vs. right) within-subjects across the repeated cue-value patterns. The order of trials as well

[3] The sample sizes in each condition were unequal due to experimental dropout. For more information, see the online supplemental materials.

as the names of stocks and experts were randomized for each participant.

Materials

We used the same hypothetical stock market game, cue validities, and cue-value patterns as described in Jekel et al. (2018). The cue-value patterns were designed in such a way that there were two versions of each pattern, one in which Option A and one in which Option B was more attractive according to iCodes (Version A and B, respectively, see Table 1). This change in attractiveness was achieved by changing the valence or availability of one or two cue values in each pattern.

Attraction Search Score. As our main interest in this experiment was participants' information-search behavior, we measured which concealed cue values were opened in each trial. To represent the manipulation of attractiveness, we calculated the Attraction Search Score as dependent variable. The score is the difference between the probabilities of showing search behavior consistent vs. inconsistent with the ASE and, thus, reflects how well participants' behavior matches the predictions of iCodes for the cue value opened first. A positive Attraction Search Score indicates that participants searched information more often for the currently attractive option. An Attraction Search Score of zero, however, indicates that participants' search was not influenced by the already available information. As the pattern version was the indicator of option attractiveness, the Attraction Search Score in this experiment was calculated with the following formula: $Attraction\ Search\ Score =$
$p(Searching\ For\ Option\ A \mid Version\ A) - p(Searching\ for\ Option\ A \mid Version\ B)$.

γ parameter. ICodes predicts that both, information's predictive strength (i.e., validity) and options' attractiveness, influence information search additively. The role of the γ parameter in iCodes is to moderate the share of the attractiveness influence during the information search. Specifically, γ represents the percentage of the attractiveness influence during information search, while the percentage of the validity influence is represented by the counter-percentage $1 - \gamma$. Within the network structure of iCodes, the relative impact of attractiveness and validity on information search is moderated by the weight of the links connecting concealed cue-value nodes with option and cue nodes, respectively. As the relative influence of validity on information search (i.e., the weight of the links connecting cue and concealed cue-value nodes) is fixed, one can calculate the weight of the links connecting option and concealed cue-value nodes (i.e., the attractiveness top-down influence) by multiplying the weight with the respective odds of γ, $w_{top-down} = w_{bottom-up} \times \frac{\gamma}{1-\gamma}$.

Procedure

The experiment was conducted in accordance with the ethical standards of the American Psychological Association (APA) and with the 1964 Helsinki declaration and its later amendments. The experiment was run online using *lab.js* (Henninger et al., 2019) and *oTree* (Chen et al., 2016). Participants first gave their consent and then continued to read the instructions of the task. Next, they worked on the decision task. In the group with attractiveness ratings, the first task in each trial was to rate the options' attractiveness. For this purpose, participants moved a continuous slider towards the option name they thought to be more attractive. The rating could take on values between -50 and 50 with a value of 0 representing that both options were equally attractive. A value of -50 meant that the option presented on the left side of the screen was more attractive, while a value of 50 meant that the option presented on the right side of the screen was more attractive.

After the rating, the procedure did not differ between experimental and control: Participants were asked to search for information and finally to decide between the two options. In each trial, they had to open at least one piece of concealed information. After their first information acquisition, participants could continue to search for information with each additional piece of information costing 0.25 Cents. The total costs for information search were deducted from the final payout of each participant. Once participants finished searching for information, they had to decide between the two options by clicking on a button below the options' names. Participants' decisions were incentivized with 2.5 Cents per correct decision as determined by a naïve Bayes' rule based on the complete cue pattern (for the naïve Bayes implementation, see Lee & Cummins, 2004). After finishing the decision task, participants were debriefed, informed about their payout, and thanked for their participation.

Results

All analyses were conducted with the statistics software *R* (R Core Team, 2020). Data and analyses scripts can be found at https://osf.io/4khmq/?view_only=22284fc9536b4590b918585f4627f365.

The effect of attractiveness ratings on the Attraction Search Score (H1)

In line with H1, the Attraction Search Score was higher in the condition with rating ($M_{WithRating} = 0.39$, $SE = 0.02$), as compared to the condition without ($M_{NoRating} = 0.28$, $SE = 0.02$), $t(187.24) = 4.03$, $p < .001$, tested one-sidedly, Cohen's $d = 0.57$.[4] Similar to previous findings (Jekel et al., 2018), we observed a strong Attraction Search Effect aggregated across conditions, $M_{ASS} = 0.33$, $t(201) = 22.51$, $p < .001$, tested one-sidedly, Cohen's $d = 1.58$. To check the robustness of these results, we ran a generalized mixed model on the trial level, which led to the same conclusions (see online supplement for detailed results).

The effect of attractiveness ratings on search probabilities (H2)

According to H2, we expected that predicted search probabilities were positively rank-correlated with the ordering of observed search probabilities per cue pattern in both conditions.[5]

[4] Due to the unequal sample sizes in the two experimental groups, we used the Welch corrected degrees of freedom.

[5] There was a mistake in the predicted ranking displayed in the preregistration, as one cue-value pattern was not correct in the a priori simulation. Corrected rankings of search-probabilities used in the article can be found in the online supplemental materials, Figure 1. For other deviations from the pre-data report, see also online supplement.

The observed rank ordering of search-probabilities showed a significant positive correlation with the predicted rank ordering in the control condition, $r_{NoRating} = .93$, $S = 46$, $p < .001$, tested one-sidedly. Yet, in the condition with attractiveness ratings predicted and observed search-probability rank orderings showed a positive but non-significant correlation, $r_{WithRating} = .28$, $S = 490$, $p = .147$, tested one-sidedly. The overall correlation was $r = .54$, $S = 2518$, $p = .002$ (two-sided test).

To test whether our a priori γ estimates were inaccurate, we re-created the predicted rankings by fitting a single γ parameter based on participants' information-search behavior for each condition (fixed $P = 1.66$ and $\lambda = 20.18$, for more details, see Jekel et al., 2018). In the experimental condition, the fitted γ parameter was $\gamma = 0.11$ indicating an attractiveness share during the information-search process around 11%, while in the control condition $\gamma = 0.07$, indicating a 7% share of attractiveness, much lower than the initial assumption.

Based on fitted γ parameters, the rank correlation of observed and predicted search probabilities was $r_{WithRating} = .69$, $S = 214$, $p = .004$ in the experimental condition and $r_{NoRating} = .91$, $S = 58$, $p < .001$ in the control condition (see online supplement Figure 2). Thus, with proper γ values, the rank orderings of predicted and observed search probabilities are positively correlated in both conditions.

The effect of attractiveness ratings on the γ parameter (H3)

We hypothesized that individually-fitted γ parameters should on average be larger in the experimental than in the control condition, reflecting a stronger attractiveness influence on information search in the former condition.

To test this hypothesis, we fitted individual γ parameters based on participants' search behavior. In addition to γ, there are two parameters in iCodes that influence information search: The P parameter and the λ parameter. The P parameter represents the individual sensitivity towards cue validity differences (Glöckner et al., 2014; Jekel et al., 2018). The λ parameter represents the individual sensitivity towards differences between activations of cue values in the model. A λ of zero would indicate that a person randomly picks which cue value to search for next. We fitted all three parameters to the data (for details of the fitting procedure, see Jekel et al., 2018).

The mean γ parameter in the experimental group was $\gamma_{WithRating} = 0.09$ ($SE = 0.008$), while in the group with no ratings the mean γ was $\gamma_{NoRating} = 0.06$ ($SE = 0.005$), $t(159.54) = 3.42$, $p < .001$, tested one-sidedly, Cohen's $d = 0.50$. Thus, in line with H3, rating option attractiveness increased its influence in the information-search process by about 50% relative to the control condition.[6]

Comparison of different Model Specifications

We argued that effects of option attractiveness are a relevant factor in information search and responsible for the observed variance in the attraction search effect. To test both assumptions more directly, we fitted and compared five different versions of iCodes that varied concerning how option attractiveness influences were implemented (see Table 2). Model 5 is the model we used for conducting the analyses of Hypothesis 3.

To compare the nested models, we calculated likelihood-ratio tests. The comparison of Model 1 and 2 indicated that including the option-attractiveness influence improves model fit, $\chi^2(1) = 3148.66$, $p < .001$. Fitting two separate γ parameters for each condition further improved model fit (Model 2 vs. Model 3), $\chi^2(1) = 159.99$, $p < .001$, indicating that γ actually captured the effect of pre-search attractiveness ratings. Additionally, accounting for individual differences beyond the experimental manipulation in the attractiveness influence further improved model fit (Model 2 vs. Model 4), $\chi^2(201) = 2056.60$, $p < .001$. Finally, the model accounting for individual differences in all three parameters, P, λ, and γ (Model 5), fitted the data better than the model with individual γ parameters and fixed P and λ parameters (Model 4), $\chi^2(404) = 6110.66$, $p < .001$. The difference in the respective model fits translated to the prediction performance when looking at the individual correlations of predicted and observed search probabilities (see Figure 2).

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[6] Support for the validity of our model fitting was provided in the online supplement.

General Discussion

In a comprehensive study, we replicated a strong attraction search effect (ASE) in both conditions. In line with the predictions of iCodes, the likelihood to search a piece of information increases with the perceived attractiveness of this option. We also identified an important moderator for the ASE. The magnitude of the effect increases if participants have a clearer impression of option attractiveness, which we induced by asking for attractiveness ratings based on partial information before active information search. Participants were more likely to search information for the preferred option when they rated the options' attractiveness before search. A mixture parameter γ that modulates the relative strength of the attractiveness influence as compared to influences of cue validity in iCodes, was shown to be sensitive to the manipulation. Including γ improved the predictive accuracy of the model. We identified reliable differences in the magnitude of the ASE between participants, which can be mapped with γ. Taking individual parameter values into account increased the prediction accuracy of iCodes in comparison to model versions with a fixed γ-parameter as proposed by Jekel et al. (2018) or a fitted global γ-parameter value for all participants. Finally, the extended iCodes model with proper γ-parameters allowed predicting differences concerning the magnitude of the ASE between different cue-value patterns, as indicated by strong correlations of predicted and observed search probabilities.

The γ parameters found in the current study indicate that information search is mainly driven by cue validity and that influences of option attractiveness are weaker by roughly factor 10. Still, there is a reliable influence of option attractiveness on information search, with around 6% in the condition without and around 9% in the condition with attractiveness ratings. The results of the model comparisons substantiate the importance of option-attractiveness influences for predicting information search.

Related search phenomena

Various information-search phenomena such as selective exposure and positive hypothesis testing show similarities to the ASE, but it is important to note relevant differences. Selective exposure or confirmation bias require a priori knowledge of the valence of information before search (Fischer & Greitemeyer, 2010), which is not required for the ASE to appear. Pseudodiagnosticity and positive hypothesis testing are investigated in the context of hypothesis-testing paradigms (e.g. Doherty et al., 1981) and are therefore closely related to the ASE. The question remains, whether these phenomena are just different instances of the same or fundamentally similar processes. A potential answer has been offered by both, Fischer and Greitemeyer (2010) and Fraser-Mackenzie and Dror (2009), who proposed dual-process accounts for attractiveness-biased information search, hinting at motivational aspects of information search (Fischer & Greitemeyer, 2010) and influences of a basic need for coherence (Fraser-Mackenzie & Dror, 2009). ICodes may add to this literature by formalizing the latter coherence-based processes during information search.

An advantage over more verbal theories of attraction-based search is that iCodes is a quantitative model. It not only predicts the existence of an effect but also makes precise, interval-scaled predictions regarding the magnitude of the attractiveness influence on search. This increases the empirical content of the model (Glöckner & Betsch, 2011; Popper, 2005) and allows for more rigorous investigation of different types of attractiveness influences on information search. Furthermore, by validating the γ parameter, our results open the possibility to measure the extent of the attractiveness influence on search and, thus, possibly aid in teasing apart different explanations for attractiveness phenomena in search. One goal for future research could be to distinguish motivational and cognitive influences on attractiveness-biased search further, to identify boundary conditions for both, and to extend iCodes to be able to capture motivational processes (cf., Shultz & Lepper, 1996).

Cognitive and Motivational Influences

The exact mechanism behind the influence of option attractiveness on information search is not yet fully known. One possible mechanism could be that participants' cognitive resources are limited and they, thus, tend to focus on their preferred option

(Evans et al., 2002; Mynatt et al., 1993). Thus, making preferences more salient to participants leads to more attractiveness-based search of information. An alternative motivational explanation would be that participants made a pre-commitment to the option and, thus, were motivated to look for (positive) information on this option (similar to the motivated reasoning described in the selective exposure literature, Fischer & Greitemeyer, 2010; Fraser-Mackenzie & Dror, 2009). A straightforward argument against this explanation is that, in our paradigm, participants do not know the valence of concealed cue values and cannot be sure that their search will confirm their current belief. Nonetheless, one could argue that participants still expect to find positive information on the attractive option due to the already available evidence pointing to this. In future research, one could try to differentiate between these two explanations and foster an integration of cognitive and motivational theories of reasoning and search.

Conclusion

The validity of cues as well as the emerging attractiveness of options jointly influence information search. People differ in the extent to which they rely on both processes when searching for information and situational manipulations that let individuals form clear impressions of options' attractiveness can further increase influences of option attractiveness as would be theoretically expected. We proposed and validated an extended iCodes model by adding a new mixture parameter γ that captures the relative importance of both influence factors on search. Extending iCodes in this way allows for a multitude of investigations of individual and situational moderators of the processes during information search. It also provides a model that allows taking into account top-down (i.e. validity/strategy driven) and bottom-up (e.g. effects of saliency, option priming) processes in search that has been called for in recent reviews (Orquin & Mueller Loose, 2013).

References

Chen, D. L., Schonger, M., & Wickens, C. (2016). oTree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97. https://doi.org/10.1016/j.jbef.2015.12.001

Doherty, M. E., Schiavo, M. B., Tweney, R. D., & Mynatt, C. R. (1981). The influence of feedback and diagnostic data on pseudodiagnosticity. *Bulletin of the Psychonomic Society*, *18*(4), 191–194. https://doi.org/10.3758/BF03333600

Evans, J. S. B. T., Venn, S., & Feeney, A. (2002). Implicit and explicit processes in a hypothesis testing task. *British Journal of Psychology*, *93*(1), 31–46. https://doi.org/10.1348/000712602162436

Fischer, P., & Greitemeyer, T. (2010). A new look at selective-exposure effects: An integrative model. *Current Directions in Psychological Science*, *19*(6), 384–389. https://doi.org/10.1177/0963721410391246

Fraser-Mackenzie, P. A. F., & Dror, I. E. (2009). Selective information sampling: Cognitive coherence in evaluation of a novel item. *Judgment and Decision Making*, *4*(4), 307–316.

Gigerenzer, G. (2001). The adaptive toolbox. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 37–50). MIT Press.

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669. https://doi.org/10.1037/0033-295X.103.4.650

Gigerenzer, G., & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. *Simple heuristics that make us smart* (pp. 3–34). Oxford University Press.

Glöckner, A., & Betsch, T. (2008). Modeling option and strategy choices with connectionist networks: Towards an integrative model of automatic and deliberate decision making. *Judgment and Decision Making*, *3*(3), 215–228. https://doi.org/10.2139/ssrn.1090866

Glöckner, A., & Betsch, T. (2011). The empirical content of theories in judgment and decision making: Shortcomings and remedies. *Judgment and Decision Making*, *6*(8), 711–721.

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? a parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666. https://doi.org/10.1016/j.cognition.2014.08.017

Henninger, F., Shevchenko, Y., Mertens, U. K., & Hilbig, B. E. (2019). Lab.js: A free, open, online study builder. *Behaviore Research Methods*. https://doi.org/10.5281/zenodo.597045

Holyoak, K. J., & Simon, D. (1999). Bidirectional reasoning in decision making by constraint satisfaction. *Journal of Experimental Psychology: General*, *128*(1), 3–31. https://doi.org/10.1037/0096-3445.128.1.3

Jekel, M., Glöckner, A., & Bröder, A. (2018). A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect. *Psychological Review*, *125*(5), 744–768. https://doi.org/10.1037/rev0000107

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the “take the best” and the “rational” models. *Psychonomic Bulletin & Review*, *11*(2), 343–352. https://doi.org/10.3758/BF03196581

McClelland, J. L., Mirman, D., Bolger, D. J., & Khaitan, P. (2014). Interactive activation and mutual constraint satisfaction in perception and cognition. *Cognitive Science*, *38*(6), 1139–1189. https://doi.org/10.1111/cogs.12146

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: I an account of basic findings. *Psychological Review*, *88*(5), 375–407. https://doi.org/10.1037/0033-295X.88.5.375

Montgomery, H. (1989). From cognition to action : The search for dominance in decision making. In H. Montgomery & Svenson, O. (Eds.), *Process and structure in human decision making* (pp. 23–49). Wiley.

Mynatt, C. R., Doherty, M. E., & Dragan, W. (1993). Information relevance, working memory, and the consideration of alternatives. *The Quarterly Journal of Experimental Psychology Section A*, *46*(4), 759–778. https://doi.org/10.1080/14640749308401038

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*(1), 190–206. https://doi.org/10.1016/j.actpsy.2013.06.003

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. https://doi.org/10.1037/0278-7393.14.3.534

Pennington, N., & Hastie, R. (1986). Evidence evaluation in complex decision making. *Journal of Personality and Social Psychology*, *51*(2), 242–258. https://doi.org/10.1037/0022-3514.51.2.242

Popper, K. (2005). *The logic of scientific discovery*. Routledge.

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Read, S. J., Vanman, E. J., & Miller, L. C. (1997). Connectionism, parallel constraint satisfaction processes, and gestalt principles: (re)introducing cognitive dynamics to social psychology. *Personality and Social Psychology Review*, *1*(1), 26–53. https://doi.org/10.1207/s15327957pspr0101_3

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488–512.

Shultz, T. R., & Lepper, M. R. (1996). Cognitive dissonance reduction as constraint satisfaction. *Psychological Review*, *103*(2), 219–240. https://doi.org/10.1037/0033-295X.103.2.219

Söllner, A., Bröder, A., Glöckner, A., & Betsch, T. (2014). Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm. *Acta Psychologica*, *146*, 84–96. https://doi.org/10.1016/j.actpsy.2013.12.007

Svenson, O. (1992). Differentiation and consolidation theory of human decision making: A frame of reference for the study of pre- and post-decision processes. *Acta Psychologica*, *80*(1), 143–168. https://doi.org/10.1016/0001-6918(92)90044-E

Thagard, P., & Millgram, E. (1997). Inference to the best plan: A coherence theory of decision. In A. Ram & Leake (Eds.), *Goal-driven learning*. MIT Press.

Thagard, P. (1989). Explanatory coherence. *Behavioral and Brain Sciences*, *12*(3), 435–502. https://doi.org/10.1017/S0140525X00057046

Table 1

Eight pairs of cue patterns with four cues and two options from Jekel et al. (2018). + represents positive cue values, − negative cue values, ? represents concealed but searchable cue value, X concealed and unsearchable cue value. Version A of patterns is displayed, cue values in parentheses represent Version B.

Pattern 1		Pattern 2		Pattern 3		Pattern 4	
Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
+	−	+ (−)	?	X	−	?	− (+)
+ (X)	+	?	?	X	− (+)	−	?
?	+	?	?	?	+	+	−
−	?	?	?	−	?	−	+
Pattern 5		**Pattern 6**		**Pattern 7**		**Pattern 8**	
Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
+ (−)	?	+ (−)	− (+)	+ (−)	− (+)	−	+
+ (−)	?	?	?	?	?	+	−
?	?	+	−	+	−	?	?
?	?	−	+	−	?	+ (?)	?

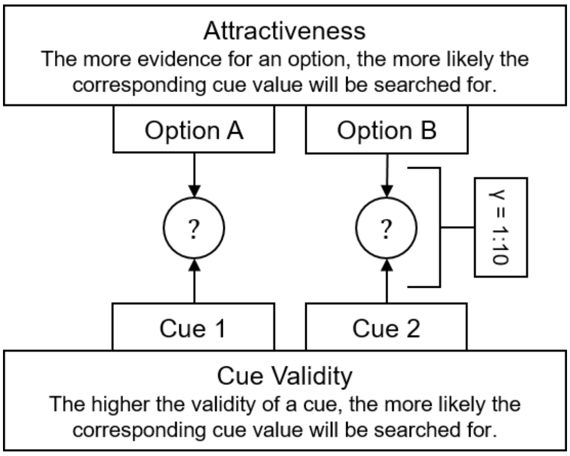
Table 2

Description of five fitted models. Models differ in whether parameters P, λ, and γ are fixed, fitted globally across participants, or fitted individually per person.

	Fitting Type		
	P	λ	γ
Model 1	fixed at P = 1.66	fixed at λ = 20.18	fixed at γ = 0
Model 2	fixed at P = 1.66	fixed at λ = 20.18	fitted globally and across conditions
Model 3	fixed at P = 1.66	fixed at λ = 20.18	fitted globally and one for each condition
Model 4	fixed at P = 1.66	fixed at λ = 20.18	fitted individually
Model 5	fitted individually	fitted individually	fitted individually

Figure 1

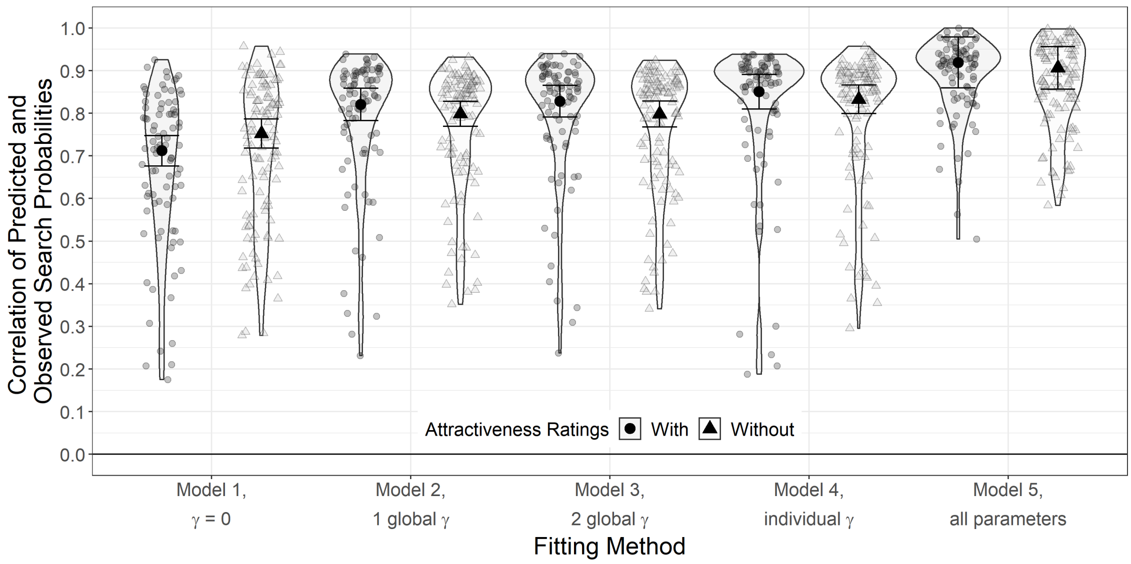
Representation of the Option Attractiveness and Cue Validity Influences in iCodes



Note. The parameter γ covers the relative strength of both influences. The default value of $\gamma = 0.09$ implies that the influence of cue validities is ten times stronger than the influence of option attractiveness.

Figure 2

Individual Pearson correlations of Fitted and Observed Search Probabilities



Note. For each fitting type (see text for model descriptions), the individual correlations are reported separately for the condition with attractiveness ratings (dark grey points) and without attractiveness ratings (light grey rectangles). The black circles and triangles represent the mean correlation, error bars represent the standard error of the mean.

Supplemental Materials

Testing an extension of the iCodes model to account for situation, person and task specific variation in the attraction search effect

Sophie E. Scharf
University of Mannheim

Marc Jekel, Andreas Glöckner
University of Cologne

Supplemental Materials

Testing an extension of the iCodes model to account for situation, person and task specific variation in the attraction search effect

Analysis of selective drop-out

More participants dropped out of the condition with attractiveness ratings than the condition without attractiveness ratings which led to unbalanced sample sizes ($N_{WithRating} = 87$ and $N_{NoRating} = 115$). Our participants provided demographic information and personality scores when registering in the Hagen Decision Lab. We could, therefore, investigate whether participants between conditions differed on those measures to assess whether selective drop-out was an issue during our study. We analyzed whether the participants differed on demographic or personality characteristics between the two conditions and whether the participants who dropped out of the condition with attractiveness ratings differ from participants who finished the experiment in the condition with attractiveness ratings.

Measures

As this analysis was exploratory in nature, we concentrated only on personality facets of the HEXACO-100 Personality Inventory scores (including altruism items, Lee & Ashton, 2018) and participants' score on the 3- and 7-item cognitive reflection test (CRT, Toplak et al., 2014). Further, we included participants' age and gender in the analyses.

Results

In a first step, we compared the participants between the experimental conditions that completed the experiment by running two sample t tests, with Welch corrected degrees of freedom. Neither the CRT scores nor the HEXACO personality scores differed significantly between the two conditions, all $ts < |1.44|$, all $ps > .149$. Additionally, the distribution of gender was not significantly different in the two conditions, $\chi^2(1, N = 195) = 0.004$, and participants did not differ in their age, $t(156.35) = 0.93$, $p = .356$.

Secondly, we tested whether participants who dropped out of the attractiveness-rating condition differed in their personality characteristics from participants who finished the experiment in the same condition. Just as before, participants did not differ significantly from each other on their CRT scores or their HEXACO scores, all $ts < |1.16|$, all $ps > .250$. The same was true for participants' age, $t(98.62) = -1.15$, $p = .253$, and gender distribution, , $\chi^2(1, N = 128) = 0.40$, $p = .526$.

Discussion

We did not find substantive differences on personality and demographic characteristics between participants in both conditions of our data set. In addition, we did not find any differences between participants who dropped out of the condition with attractiveness ratings and participants who completed the experiment in the attractiveness-rating condition.

Results of Generalized Mixed Model (H1)

To substantiate the results of our first hypothesis, we also ran a generalized mixed model to analyze search behavior on the trial versus aggregate level. The dependent variable was whether participants searched for Option A or Option B in any given trial. As predictors we included the cue-pattern *version* and the experimental *condition*. Both predictors were effect-coded: Version A received the weight $+1$, Version B the weight -1; the condition with attractiveness ratings received the weight $+1$, the condition without attractiveness ratings -1. Random intercepts for participants were included to account for inter-individual variance. Multilevel analyses were run using the *lme4* package (Bates et al., 2015), significance tests for multilevel models were conducted using the *lmerTest* package (Kuznetsova et al., 2017). The results of this mixed model showed a statistically significant main effect of *version*, $b = 0.70$, $z = 51.93$, $p < .001$, such that participants were more likely to search for Option A in Version A in which Option A was more attractive than in Version B in which Option B was more attractive. Specifically, the probability to search for Option A in Version A is predicted to be 68.2% in comparison to 34.6% in Version B. Further, there was a main effect of *condition*, $b = -0.04$, $z = -2.55$, $p = .011$, such that participants were more likely to search for Option A in the condition without attractiveness ratings before search (predicted probability of 52.6%) than in the condition with attractiveness ratings (predicted probability of 50.5%). Lastly, there was a significant interaction of the two factors *version* and *condition*, $b = 0.13$, $z = 9.47$, $p < .001$. This interaction indicated that participants were more likely to search for Option A in Version A if they rated options' attractiveness before search than if they did not rate options' attractiveness. Specifically, the probability of searching for Option A increased in the experimental group by 39.1% while the increase in the control group was 27.8%. Thus, the results of the generalized linear mixed model supported the preregistered results.

Deviations from pre-data report: Changes in modelling information-search behavior

This project was pre-registered with a pre-data report at https://osf.io/qrwmz/ (Scharf et al., 2018). In this pre-data report, we report a small a priori simulation study to derive predictions based on the γ parameter—referred to as *rho* parameter in the pre-registration (see https://osf.io/4khmq/?view_only=22284fc9536b4590b918585f4627f365)—for the cue patterns used in the study.

When fitting γ based on participants' search behavior after data collection was completed, we changed how γ was parameterized. Our initial approach was to fit γ as the factor of how much more weight the predictive strength of the information, i.e., validity, receives during the search process compared to the options' attractiveness. This factor changes the weight of the links between option and concealed cue-value nodes and was fixed to 10 in Jekel et al. (2018)'s studies, indicating that these links were 10 times weaker than the link between cue and cue-value nodes (0.1 and 0.01 respectively, for more details on the exact model implementation, see Jekel et al., 2018). This parameterization, however, entailed the problem that possible values range from 1 (the weight of the option-to-cue-value node link is equal to the cue-to-cue-value link) to infinity, making the attractiveness influence on information search infinitesimally small. This characteristic led to issues with fitting the model when the individual attractiveness influence was virtually non-existent and, thus, γ parameters became very high.

Due to these technical issues, we re-parameterized γ to represent the relative share of the attractiveness influence compared to the validity influence on information search. With this parameterization, equal validity and attractiveness influences would be represented by $\gamma = 0.5$ (or odds of 1:1). The default γ parameter that represents a ten times stronger validity influence than attractiveness influence would be $\gamma = 0.09$, representing around 9% of attractiveness influence (or odds of 1:10).

Another aspect changed in the fitting procedure compared to the pre-data report:

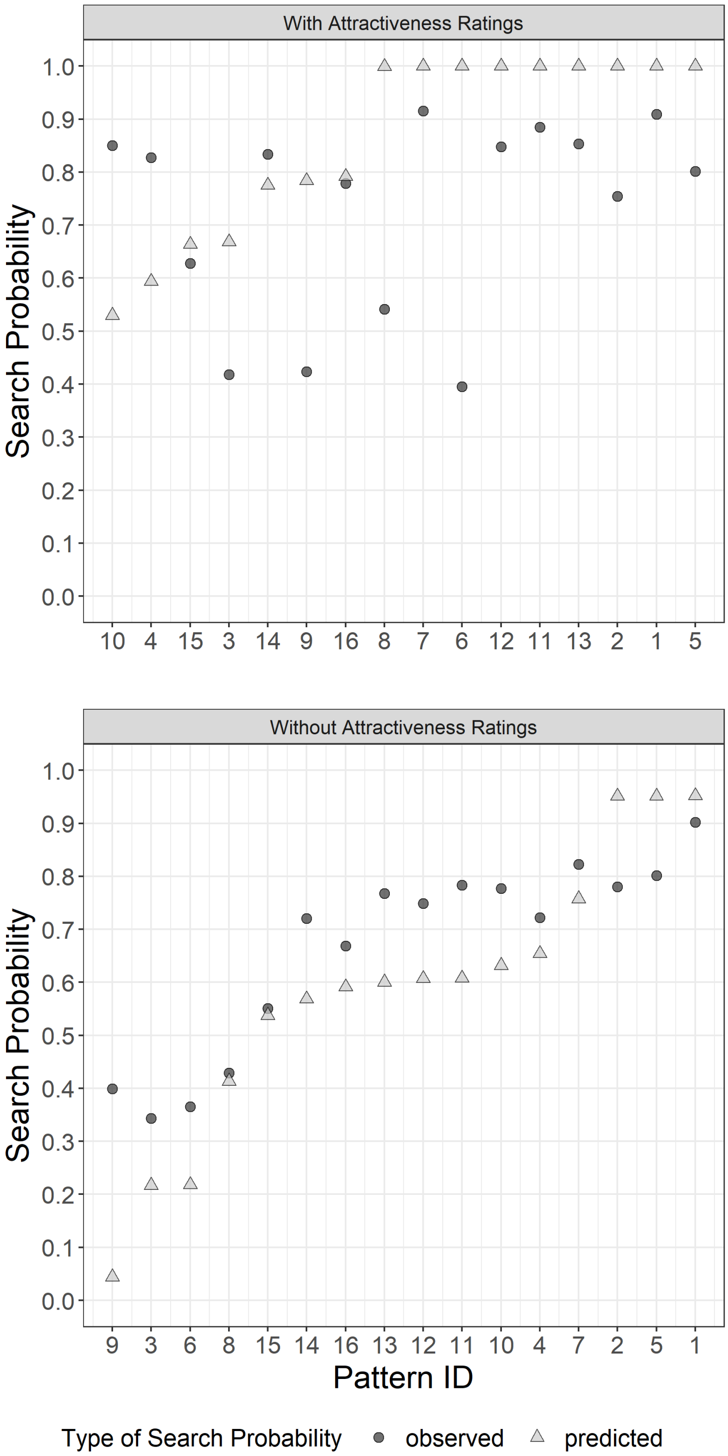
In the pre-data report we stated that we would only fit γ and P parameters and use a fixed λ_{search}. For this paper, however, we fitted λ_{search} to capture individual differences in search behavior.The reason behind this change was that it was commented during a conference that it is possible that the three parameters may not be entirely independent from each other and that consistently not fitting one of the parameters might distort the results. We, therefore, decided to either fix both, P and λ, or fit both parameters.

Illustration of Results for Hypothesis 2

The predicted search-probability ranking as derived from a simulation of the model did not correlate significantly with the observed search probabilities in the condition with attractiveness ratings (see Figure 1). To test whether the differences of parameter values between conditions were set at too extreme values in the a priori simulations, we replicated this analysis with predicted rankings based on fitted parameters. Specifically, we fixed the P and λ parameters to the average values reported in Jekel et al. (2018), $P = 1.66$ and $\lambda = 20.18$ and fitted one γ parameter per condition. The γ parameters were $\gamma_{WithRating} = 0.11$ and $\gamma_{NoRating} = 0.07$. With the fitted parameters, the correlation of predicted and observed search-probability rankings was significant and positive in both conditions (see Figure 2).

Figure 1

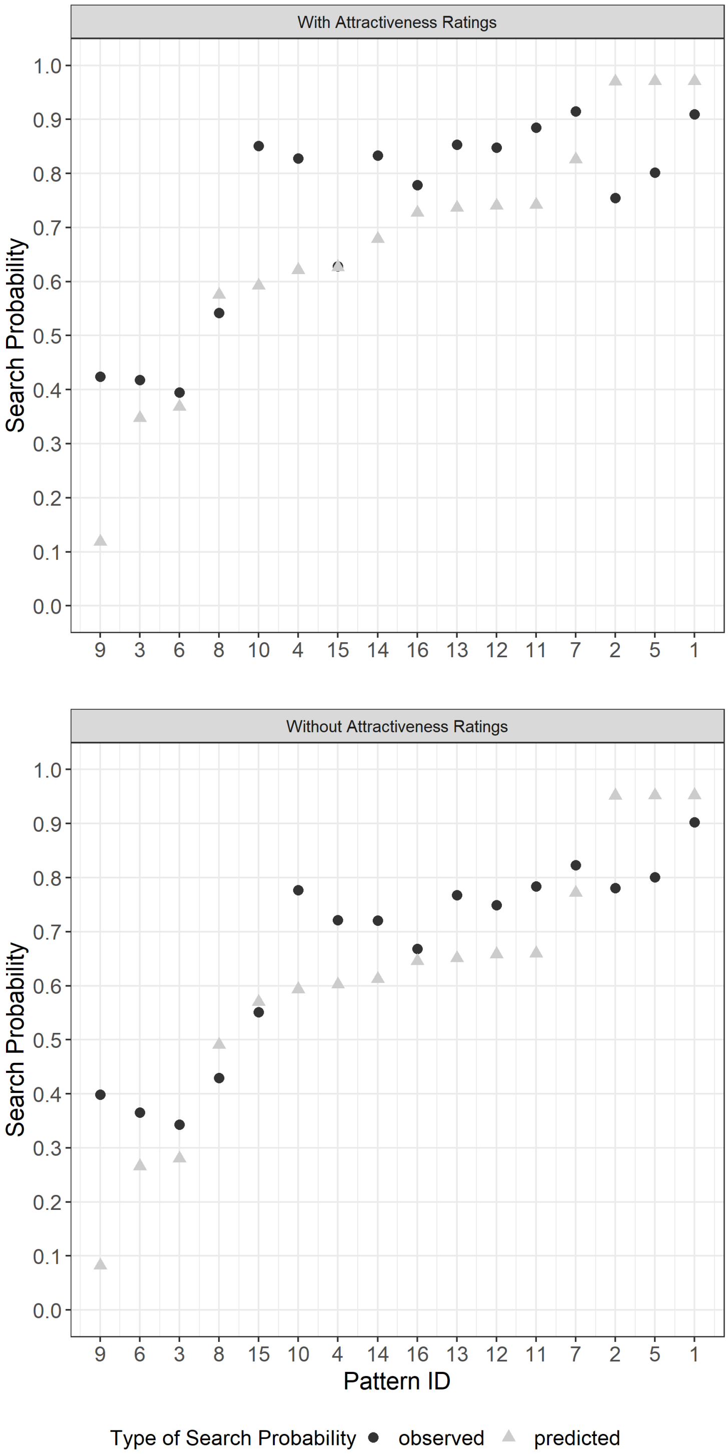
Comparison of Predicted and Observed Search Probabilities per Cue-Value Pattern



Note. Pattern IDs on the x axis represent the eight cue-value patterns in two versions, with Pattern 1 in Version A represented as 1, Pattern 1 in Version B represented as 2, Pattern 2 in Version A represented as 3, and so on. Dark grey points represent predicted search probabilities based on $\gamma = 0.5$ in the attractiveness-rating condition (upper panel) and on $\gamma = 0.05$ in the condition without attractiveness ratings (lower panel). Light grey triangles represent the observed search probabilities in both conditions.

Figure 2

Comparison of Fitted and Observed Search Probabilities per Cue-Value Pattern



*Note.*Pattern IDs on the x axis represent the eight cue-value patterns in two versions, with Pattern 1 in Version A represented as 1, Pattern 1 in Version B represented as 2, Pattern 2 in Version A represented as 3, and so on. Dark grey points represent predicted search probabilities based on a fitted $\gamma_{WithRating} = 0.11$ in the attractiveness-rating condition (upper panel) and on a fitted $\gamma_{NoRating} = 0.07$ in the condition without attractiveness ratings (lower panel). Light grey triangles represent the observed search probabilities in both conditions.

Validity of Model Fitting Procedure

The attractiveness ratings should only affect the influence of option attractiveness during information search but not the P and λ parameters. Indeed, both parameters did not show an effect of the experimental manipulation, $M_{P\ NoRating} = 1.47$, $M_{P\ WithRating} = 1.42$, $t(191.00) = -0.43$, $p = .668$, $BF = 0.17$ and $M_{\lambda\ NoRating} = 67.74$, $M_{\lambda\ WithRating} = 74.73$, $t(149.24) = -0.43$, $p = .667$, $BF = 0.17$, tested two-sidedly, providing further support for the validity of the fitting procedure.

We further ran a split-half cross prediction to test the validity of our model fitting and to detect potential overfitting. We split the experimental data set in a training and a test set of equal size. From the 128 trials of each participant, we selected 64 trials by choosing four of the eight repetitions of each pattern in each version randomly. With this procedure both, the training and test set, contain the same cue patterns. We then fitted the individual γ, P, and λ parameters with the training data set and used these parameters to predict information-search frequencies in the test set. The predicted information-search frequencies correlated positively with the observed information-search frequencies in both conditions, $r_{WithRating} = .92$, 95%CI [.87, .94], and $r_{NoRating} = .86$, 95%CI [.81.90], indicating that our estimation procedure was robust and did not involve overfitting.

References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Jekel, M., Glöckner, A., & Bröder, A. (2018). A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect. *Psychological Review*, *125*(5), 744–768. https://doi.org/10.1037/rev0000107

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Lee, K., & Ashton, M. C. (2018). Psychometric properties of the HEXACO-100. *Assessment*, *25*(5), 543–556. https://doi.org/10.1177/1073191116659134

Scharf, S. E., Franke, N., Jekel, M., Glöckner, A., & Bröder, A. (2018). *Study 4: Attractiveness ratings and the attraction search effect.* https://osf.io/4khmq

Toplak, M. E., West, R. F., & Stanovich, K. E. (2014). Assessing miserly information processing: An expansion of the cognitive reflection test. *Thinking & Reasoning*, *20*(2), 147–168. https://doi.org/10.1080/13546783.2013.844729

Coherence influences on attention allocation and visual information search in decisions with open information displays

Sophie E. Scharf, Arndt Bröder
University of Mannheim

Marc Jekel, Andreas Glöckner
University of Cologne

Author Note

This research was supported by a grant of the German Science Foundation (Deutsche Forschungsgemeinschaft, DFG) awarded to Andreas Glöckner (GL 632/5-1) and Arndt Bröder (BR 2130/13-1). We thank Rima-Maria Rahal, Pascal Kieslich, and Nicole Franke for their support in implementing the studies. The article has not been made available on any online depository or website previously. Predata reports and data for the experiments can be found at https://osf.io/j7v9a/?view_only=509578b5215e4115a46cf923cf2b7f40 (Experiment 1) and https://osf.io/ykjqr/?view_only=c3c25c7809ae4638aa8d5a9702ad2dcf (Experiment 2). Correspondence concerning this article should be addressed to Sophie E. Scharf, Department of Psychology, School of Social Sciences, University of Mannheim, 68131 Mannheim, Germany. E-mail: sophie.scharf@staff.uni-mannheim.de

Abstract

The integrated coherence-based decision and search model (iCodes; Jekel et al., 2018) predicts that both the validity of information and the coherence of the information with the emerging preferred option influence attention allocation in decision making. In two pre-registered experiments (total $N = 107$), we tested qualitative predictions of iCodes by analyzing participants eye movements while repeatedly deciding in a hypothetical stock-market game. The results show that the previously observed attraction search effect generalizes from active, deliberate information search to automatic attention allocation in visual search. We observe a strong and robust *attraction attention effect*, in that the fixation likelihood of new information increases with the attractiveness of the respective option. The general effect of coherence on attention allocation in the decision task predicted by iCodes could be confirmed as well. Solely the predicted *late coherence effect* was not supported, as we did not observe an increase of the coherence influence on attention allocation over the course of a trial. The results overall highlight the importance of coherence for attention allocation during decision making and provide support for coherence-based models of decision making such as iCodes.

Keywords: Coherence; Attention Allocation; Parallel Constraint Satisfaction Network Model; Attraction Search Effect; Eye Tracking

Coherence influences on attention allocation and visual information search in decisions with open information displays

Past research has demonstrated that the coherence of information, that is, the consistency of information with the currently attractive choice option, influences decision-making processes (Glöckner & Betsch, 2008a; Holyoak & Simon, 1999; Thagard, 2000). Specifically, it has been demonstrated that participants integrate coherent information more quickly (Glöckner & Betsch, 2012), overweight coherent and underweight incoherent information to support the favored option (Glöckner et al., 2010), and use even irrelevant information if it changes the coherence of the decision situation (Söllner et al., 2014). With the *parallel constraint satisfaction model of decision making* (PCS-DM), Glöckner et al. (2014) introduced a formalized computational model that can account for this information distortion and additionally makes precise predictions with regard to choices, decision times, and confidence judgments. Yet, PCS-DM and its predecessors (Glöckner & Betsch, 2008a) have been criticized for not including a fully specified model for information-search processes and attention (Marewski, 2010). Thus, the model's ability to make precise and dynamic process predictions for attention allocation in decision tasks is limited (Orquin & Mueller Loose, 2013).

Jekel et al. (2018) addressed these criticisms by proposing an extension of PCS-DM, the *integrated coherence-based decision and search model* (iCodes). By extending the coherence-based decision process to also include information search, they could demonstrate that the coherence of information also plays a role in active information search. In their studies, participants were more likely to search for information for the currently attractive option in probabilistic-inference tasks. This *attraction search effect* for active information search (i.e., collecting information by using the mouse pointer) was strong in magnitude, robust over various paradigms, and replicated in later studies (Scharf et al., 2019). It, however, remained unclear, whether the attraction search effect is limited to arguably more deliberate acts of active information search or also generalizes to probably more automatic patterns of visual attention in paradigms in which all information is instantly available, resulting in an *attraction attention effect* (details below). The goal of this article is to test iCodes's ability to also predict patterns of visual search for information (i.e. attention) as measured via eye-tracking in the same probabilistic-inference tasks. We specifically aim at testing whether an attraction attention effect exists as well as testing iCodes's predictions about the coherence influence on attention allocation and its predicted time dynamics in general. We do so by analyzing participants' gaze direction in relation to the coherence of the information presented. In the following, we first present a short overview of the current state of research on attention during decision making and search. We, then, introduce iCodes and derive its predictions for attention allocation.

Attention allocation during decision making and search

Visual attention plays an important role during decision making not only as a process of passive information uptake but also as active part in the construction of the mental representation of decisions (Orquin & Mueller Loose, 2013). In their comprehensive review, Orquin and Mueller Loose (2013) elaborated on different aspects of the interplay of attention and decision making and search. On the one hand, attention is influenced due to bottom-up processes during decision making (Orquin et al., 2013), that is, due to automatic attention driven by characteristics of the stimuli (cf. Theeuwes, 2010). Several studies measuring eye movements showed this stimulus-driven attention allocation, such that visually salient alternatives (Lohse, 1997; Milosavljevic et al., 2012) as well as visually salient attributes (Bialkova & van Trijp, 2011) were fixated more often over the course of a decision. On the other hand, attention is also guided by top-down processes (Orquin et al., 2013), that is, it is guided toward task- and goal-relevant stimuli. For instance, studies showed that information of high importance or high utility to a decision was attended to preferentially (Glöckner & Herbold, 2011; Glöckner et al., 2014; Meißner & Decker, 2010; Orquin et al., 2013; Reisen et al., 2008). Additionally, there are down-stream effects of attention on decision-making such as, for instance, described in the gaze cascade effect (Shimojo et al., 2003). This effect describes a pattern of gaze behavior such that the number of fixations on the chosen alternative increases over time in the decision-making process (e.g., Atalay et al., 2012; Fiedler & Glöckner, 2012; Glaholt & Reingold, 2009).

In light of the importance of attention during decision-making processes, several decision-making models have been evaluated with regard to their predictions for attentional patterns during decision making (Orquin & Mueller Loose, 2013). The most prominent class of models in the decision-making literature that have been successful in predicting choices based on attention and aspects of attention allocation are evidence accumulation models (Busemeyer & Johnson, 2004; Krajbich et al., 2010; Thomas et al., 2019; but see also Hausmann & Läge, 2008; Lee & Cummins, 2004, for evidence accumulation models outside the realm of eye tracking). Among the evidence accumulation models, the *attentional drift diffusion model* (aDDM, Krajbich et al., 2010; Krajbich & Rangel, 2011) is the most prominent for predicting attention allocation. These models assume that, when decision makers fixate one of the options under consideration, they accumulate evidence for it and choose an option, once the accumulated evidence for it reaches an individual decision threshold. The speed of this evidence-accumulation process for each option is assumed to be a function of the option's relative value. A core prediction of aDDM that follows from its proposed decision process is that the last fixation will be on the subsequently chosen option which is well in line with the findings on the gaze-cascade effect (Shimojo et al., 2003). With regard to information search, the original aDDM assumes that information is fixated stochastically and that the fixation pattern does not change over the course of a decision (Krajbich et al., 2010; Krajbich & Smith, 2015).

While evidence accumulation models generally fared well in predicting attention allocation during decision-making overall (cf. Fisher, 2017; Krajbich et al., 2012; Krajbich & Rangel, 2011; Smith & Krajbich, 2019; Tavares et al., 2017), their predictions of the (visual) information-search process as mainly stochastic within a trial appear to be too simplistic to be an accurate description of attention allocation during decision making (cf. Orquin & Mueller Loose, 2013). For example, studies have shown that fixations can be categorized into attention phases over the course of a decision (e.g., Glaholt & Reingold, 2011; Reutskaja et al., 2011; see also Krajbich et al., 2010; Krajbich et al., 2012). Further, aDDM currently does not make fine-grained predictions about top-down and bottom-up influences on attention on the attribute-level during information search (cf. Krajbich et al., 2012; Orquin & Mueller Loose, 2013). As a response, more recent extensions of the aDDM have, therefore, incorporated a value-based prediction of attention, in that the probability of fixating an option increases with its accumulated value already early in the decision process (Gluth et al., 2020). In addition, alternative evidence accumulation models, such as Decision Field Theory (DFT, Busemeyer & Johnson, 2004) assume that more important information is fixated with a higher likelihood. Taken together, while evidence accumulation models have been successful in predicting attention allocation during decision making, they lack in their precision for predictions for (visual) information search and its interplay with top-down and bottom-up processes.

Coherence-based information search

Another model class discussed in the decision-making literature are parallel constraint satisfaction models (e.g., Glöckner & Betsch, 2008a; Holyoak & Simon, 1999; Read et al., 1997; Thagard & Millgram, 1997). However, as already stated above, these models and even the fully specified PCS-DM model (Glöckner et al., 2014), do not explicitly model attention allocation on information in decision tasks and, similar to evidence accumulation models, do not make fine-grained predictions for attention allocation during information acquisition (Orquin & Mueller Loose, 2013).

Addressing the lack of formalized information-search predictions, Jekel et al. (2018) proposed the integrated coherence-based decision and search model (iCodes) as an extension of the PCS-DM model (Glöckner et al., 2014). Just as the PCS-DM model, the underlying idea of iCodes is that information search and decision making are best represented by a coherence-maximization process that increases the coherence of the decision situation. Once a certain level of coherence is achieved, new information is searched or a choice is made. The basis of this coherence-maximization process is a network that represents the information of a probabilistic-inference task. In these tasks, decision makers have to choose between two or more options based on the information (or cue values) given by cues that differ in their predictive quality (or validity, see also Gigerenzer & Goldstein, 1996, for a definition of cue validity) with regard to the decision criterion. The cue values can either be already available or still concealed and searchable. In iCodes's network, options, cues, and cue values are represented as nodes that are connected via links (see Figure 1 A).

The dynamic allocation of attention on cue values is represented as an iterative spread of activation across the links, initiated by the source node on the bottom of the network. From the source node, activation spreads to the cue nodes and from there to the cue-value nodes, each time proportionally to their respective validities. As only already available cue values carry information about the options, the spread of activation continues to the options only from nodes representing open cue values, while nodes of concealed cue values only receive activation via unidirectional links.[1] If the already available information in a decision task supports an option, the activation of the respective option node increases. Due to an inhibitory link between the option nodes, the increase in activation of one option node automatically leads to a decrease of activation in the other option node(s) representing a forced choice between the options. The spread of activation continues from the option nodes back to the cue-value nodes which increases the activation of nodes that represent cue values with information on the currently preferred option and decreases the activation of cue-value nodes of the currently non-preferred option. Again, as nodes of concealed cue values are only connected via unidirectional links, the spread of activation continues back only from the open cue-value nodes to the cue nodes and finally to the source node, which concludes one model iteration. This spread of activation continues until the activation levels at

[1] Similar to PCS-DM, except for links connecting to concealed cue-value nodes, all other links are bidirectional.

the nodes stabilize (i.e., do not change substantially).[2]

iCodes predicts just as PCS-DM that, after the network settled into a stable state, the option which received the most activation after this process will be chosen (Jekel et al., 2018). Information search is predicted in a similar way in that iCodes predicts that the concealed cue value (node) that received the most activation will be searched for. Importantly, nodes that represent concealed cue values are connected to cue and option nodes via unidirectional links, therefore, their final net input for those nodes is the sum of the activation they receive from cues and from options. As already detailed above, the activation cue-value nodes receive from cues is proportional to the respective cue's validity such that nodes representing cue values that stem from more valid cues receive more activation than nodes that stem from less valid cues. Thus, all else being equal, the more valid concealed information should be searched for according to iCodes. The activation cue-value nodes receive from the options on the other hand is mainly determined by the already available evidence for the options such that cue values that have information on the currently favored option receive more activation than those that have information on the currently unfavored option. Thus, iCodes predicts that, again all else being equal, cue values that have information on the currently more attractive option are more likely to be searched for.

iCodes also predicts process measures, such as decision- and information-search times by the number of iterations it takes the network to stabilize. With regard to attention allocation, the underlying assumption is that the activation at the cue-value node level can be translated behaviorally to the probability of attending to the respective cue values. Thus, iCodes predicts that the spread of activation through the network representing the decision task mirrors the distribution of attention in said task. Therefore, relative differences in activation levels between open cue-value nodes should map onto relative differences in the number of fixations on open cue values. This assumption was supported already for active information search (cf. the attraction

[2] For the full formalization of the coherence-maximization process and the iterative spread of activation, please refer to Jekel et al. (2018).

search effect, Jekel et al., 2018) but has yet to be shown for eye movements as indicator of search.

Jekel et al. (2018) tested iCodes's prediction for active information search, that they coined the attraction search effect, in a mouse-lab setting and found that participants preferentially searched for new information describing the attractive option in three experiments and the data of five re-analyzed studies. Additionally, conceptual replications showed tha the attraction search effect generalized to different semantic contexts, cue-value constellations, and presentation formats (Scharf et al., 2019). Further, situational and interindividual differences in the strength of the attraction search effect could be captured with a model-inherent parameter that modulates the relative strength of the attractiveness influence compared to the validity influence on information search (Scharf et al., 2021).

iCodes predictions for attention allocation

As stated above, the underlying assumption behind predicting gaze behavior during decision making with iCodes is that the differences in activation of the cue-value nodes can be translated to differences in attention allocation on the cue values. More specifically, cue values whose nodes retained high activation levels should be fixated preferentially compared to cue values whose nodes did not retain high activation levels.

A straight-forward transfer of iCodes predictions to attention allocation is possible with the already established attraction search effect (Jekel et al., 2018). As iCodes predicts a tendency to search for new information describing the currently attractive option first, there should also be a tendency to fixate newly revealed information describing the currently attractive option first. We coined this prediction the *attraction attention effect* (see Figure 1 B for a visualization of the prediction). Following the predictions of the attraction search effect and the attraction attention effect, our first hypothesis is as follows:

(H1) Newly revealed cue values that describe the more attractive option should have a higher probability to be fixated first than newly revealed cue values describing the less attractive option.

In addition, iCodes predicts that the nodes of cue values that contain information supporting the currently preferred option should receive additional activation from the option nodes compared to nodes of cue values describing the currently non-preferred option. Thus, information that is coherent with the attractive option, i.e. supports the attractive option or opposes the unattractive option, should receive more activation than incoherent information and should be fixated more often. We call this prediction the *coherence attention effect* (see Figure 1 B for a visualization of the prediction) and our second hypothesis is the following:

> (H2) Cue values that support the attractive option (= coherent) receive more attention than cue values that do not support the attractive option (= incoherent).

A special case of the coherence attention effect applies to newly revealed information of a cue that does not discriminate between the options. Non-discriminating cue values from the same cue share the same valence and validity, thus, they either both support or contradict their respective option. These cue values are, therefore, uninformative for the decision and should be ignored from a rational perspective. The only difference between the two indiscriminatory cue values is that one is a feature of the currently attractive option and the other is not. Thus, even though these cue values share the same valence and validity, one cue value is coherent and the other one is not. Due to the activation that stems from the options, iCodes predicts that the coherent cue value of a non-discriminating cue (+ on the attractive option, − on the unattractive option) should be fixated more often than the incoherent cue value, as it receives more activation from the currently preferred option. This prediction is reflected in the following hypothesis:

> (H2a) The cue value from a non-discriminatory cue-value pair that has positive information describing the attractive option (+) or negative information describing the non-attractive option (−) should receive more

attention than the cue value that supports the non-attractive option (+) or does not support the attractive option (−).

iCodes also makes predictions about the changes of attention allocation over the course of a trial. Due to the model structure, cue-value nodes receive activation from the cue nodes first during the iterative spread of activation. Thus, the validity of cues is the first influence on the relative differences in cue-value nodes' activation levels and should therefore be the main influence on fixation patterns in the beginning of the trial before backward activation from the options kick in. Which option is favored by the currently available evidence only takes shape later in the information-search process, when the network has started to integrate the information. Therefore, the coherence influence on gaze patterns is predicted to appear towards the end of the trial as then the cue-value nodes receive more activation from the option nodes resulting in the prediction that the probability of fixating coherent cue values should increase. We coin this prediction the *late coherence effect* (see Figure 1 C for a visualization of the prediction) as formulated the following hypothesis:

(H3) In the beginning of a decision trial, attention is mainly allocated to cues corresponding to their respective validities (= cue values of more valid cues receive more attention). Towards the end of a decision trial, attention is focused on information that is coherent with the favored option (= cue values supporting the preferred option receive more attention).

Last but not least, iCodes also predicts the gaze cascade effect (Shimojo et al., 2003). During the iterative spread of activation, the option node that is predicted to be chosen receives more and more activation, just as the cue-value nodes supporting this option. Therefore, the cue values of the finally chosen option should be fixated with an increasing probability over the course of a trial.[3] Hence, the final hypothesis we test is as follows:

[3] Note, that this prediction is conditional on the coherence of information. Only if the option, that is subsequently predicted to be chosen, is also described by more coherent (and more valid) information than the alternative option, iCodes actually predicts the gaze cascade effect. Thus, iCodes predicts an

(H4) Over the course of a decision trial, attention is allocated with increasing probability to the subsequently chosen option.

Taken together, iCodes makes precise predictions about attention allocation, its determinants, and its temporal dynamics. No other model that we are aware of predicts that the coherence of information influences attention allocation and information search (without auxiliary assumptions). To test iCodes's predictions for visual search, we conducted two experiments utilizing eye tracking to measure participants' gaze behavior.

Experiment 1

In the first experiment, we focused on testing the attraction attention effect (AAE) as the attentional equivalent to the attraction search effect (H1). We, thus, were interested in whether participants showed a tendency to fixate information describing the currently attractive option first. For this purpose, we utilized a hypothetical stock-market game (cf. Jekel et al., 2018) in which experts (i.e. cues) with different validities provide dichotomous recommendations (i.e. cue values: good vs. bad) about stocks (i.e. options). The cue-value pattern, that is, the constellation of expert recommendations, were adapted from Bröder et al. (2021, see also Table 1) and trials were constructed such that one stock was always more attractive than the other given the initially available evidence. We also adapted the two-stage experimental design from Experiment 2 by Bröder et al. (2021) that consisted of a rating phase during which participants rated which option was currently more attractive and a decision phase during which participants decided for one of the options. In the rating phase, the cue values of one cue were still concealed and were subsequently opened and available to the participants in the decision phase. Using this two-stage design allowed us to observe whether the first fixation was on new information describing the currently preferred

interaction of the gaze cascade effect with the coherence of information. In the following, we restricted our analyses to the prediction of the (main) gaze cascade effect, as we did not manipulate the amount of coherent information per option. For tentative results regarding the predicted interaction effect in the two reported experiments, see the online supplement.

option, as participants already developed a preference for one of the options during the rating phase. It also allowed us to observe participants' fixations without distortions of the gaze-behavior due to, for example, reading direction, as participants were already familiar with the decision situation and the location of the to be revealed cue values.[4] Thus, our main goal in Experiment 1 was to test whether participants fixated the newly revealed cue value on the attractive option first during the decision phase. While not the main focus of this experiment, we also tested whether participants attended to coherent information preferentially (coherence attention effect, H2 & H2a), whether the coherence influenced on attention changed over the course of a trial (late coherence effect, H3), and whether the probability to attend to the subsequently chosen option increased over the course of a trial (gaze cascade effect, H4). The experiment was preregistered and a pre-data report detailing the hypotheses, methods, and planned analyses for this experiment is available at: https://osf.io/j7v9a/?view_only=509578b5215e4115a46cf923cf2b7f40.

Methods

Design and Participants. In this experiment, we manipulated the valence of the revealed cue values during the decision phase in that they were either both positive, both negative, and one negative for the left option and one positive for the right option or vice versa. Thus, we had four different levels of the newly revealed cue values during the decision phase. Our design was, therefore, a one factorial within-subjects design (non-discriminating both positive vs. non-discriminating both negative vs. discriminating and supporting attractive option vs. discriminating and supporting unattractive option).

We ran a pilot experiment with $N = 12$ participants to test the setup of the eye tracker and to estimate effect sizes for determining the required sample size. The pilot

[4] In addition, the rating phase should boost the effect of option attractiveness on information search (cf. Bröder et al., 2021; Scharf et al., 2021), increasing our chances of finding support for the attraction attention effect.

revealed large effects for the attraction attention effect (H1, Cohen's $d_{AAE} = 2.21$) and the coherence attention effect (H2, Cohen's $d_{CAE} = 2.21$) as well as a medium-sized effect for the coherence attention effect for non-discriminating, newly revealed cue values (H2a, Cohen's $d_{CAEindscrim} = 0.44$). We used the latter effect size to conservatively determine the required sample size for Experiment 1. To be able to detect a medium effect of Cohen's $d = 0.44$ with a one-sided, one-sample t test and assuming $\alpha = \beta = .05$, the required sample size is $N = 58$ (according to G*Power, Faul et al., 2007).

We collected complete data-sets from 60 participants. We discarded the data from two participants, as they moved away from the head-rest during the experiment without the possibility to re-calibrate them afterwards, and from one participant, as they later indicated that they were underaged. Thus, our final sample consisted of 57 participants (41 female, 1 non-binary, $M_{age} = 24.53$, range: 18-34). Participants received a base-payment of 5 Euro for participating in the study and could earn extra money depending on their choices. For every correct decision, participants received 8 Cents, thus, they were able to earn up to 10.24 Euro additionally to the show-up fee (average total payoff $M_{payoff} = 14.38$ Euros, approx. USD 17.46, range: $12.00 - 15.10$ Euros).[5]

Materials. For this experiment, we used the cue-value patterns from Bröder et al. (2021, see also Table 1).[6] The validities of the cues were .90, .80, .70, and .60, and cues were always presented from top to bottom in order of their validity. The patterns were constructed such that Option A was more attractive than Option B. We counterbalanced whether Option A or B was presented on the left side or on the right side of the screen. For our experiment, the cue values of one cue were concealed during the rating phase and were revealed during the decision phase. The valence of the revealed cue values was manipulated such that they were either both positive (+ +),

[5] Correct decisions were determined according to the naïve Bayes rule (cf. Lee & Cummins, 2004). Pay offs were rounded up to 10 Cents.

[6] There was a mistake in the table of patterns reported in the pre-data report, as the options for Pattern 1, 6, and 8 were switched. The table presented here is the correct table.

both negative ($- -$), or they discriminated between options such that they supported either the attractive or the unattractive option ($+ -$ vs. $- +$). Each pattern was presented twice such that Option A was presented equally often on the left and the right side of the screen. We pseudo-randomized the order of cue-value patterns, such that at least four trials were presented between pattern repetitions. Over the course of the experiment, participants worked on a total of 128 trials (8 cue patterns x 4 versions of opened cue values x 2 counterbalancing of option side x 2 repetitions of each combination).

Measures. During the rating phase of the experiment, we measured which option participants rated as the more attractive option. Participants gave their rating on a 6-point scale ranging from "1 - the left option is much more attractive." to "6 - the right option is much more attractive". In the subsequent decision phase, we recorded which option participants chose and whether this option was correct.[7]

Eye-movement data were collected with a Tobii T120 for both eyes with a sample rate of 119 Hz and an accuracy of about 0.5° using a screen with a resolution of 1280 x 1024 pixels (size: 33.8 x 27.1 cm). We defined eight non-overlapping areas of interest (AOI) around the cue values on each screen (± 75 pixels from the cue-value center). Our main eye-tracking variable of interest was which AOIs participants fixated over the course of the decision trial.

We calculated two indices of participants' fixation behavior to test our hypotheses (cf. Jekel et al., 2018). For testing the attraction attention effect (H1), we defined the attraction attention score (AAS) that represents the difference in the probabilities of fixating newly revealed information in the decision phase on the attractive vs. the unattractive option first, similar to the attraction search score in Jekel et al. (2018). We determined which option was attractive based on iCodes's prediction for choice with fixed parameters (i.e., $P = 1.9$, cf. Glöckner et al., 2014). As this score pertains to fixations on newly revealed information, we calculated it based on fixation data from

[7] The correct choice was determined according to the naive Bayes formula (see Jekel et al., 2012; Lee & Cummins, 2004).

the decision phase of the experiment. The AAS was calculated as follows:
$AAS = p(first\ fixation\ on\ new\ information|attractive\ option) -$
$p(first\ fixation\ on\ new\ information|unattractive\ option)$.[8] Positive AAS scores represent fixation behavior that is consistent with the prediction of the attraction attention effect.

For testing the coherence attention effect (H2), we formulated the coherence attention score (CAS) that represents the difference of the relative frequency of fixating coherent information and the relative frequency of fixating incoherent information during a trial. Information is coherent if it supports the attractive option as predicted by iCodes (+ on attractive option, − on unattractive option, again based on a fixed $P = 1.9$). We calculated this score based on fixation data from the decision phase. As the number of coherent vs. incoherent cue values differed between patterns, we normalized the relative fixation frequency with the total number of coherent vs. incoherent cue values in this cue pattern. Thus, the CAS represents the difference of the mean relative frequencies of fixating a coherent vs. an incoherent cue value, $CAS = \frac{f(fix\ coherent\ cue\ value)}{n_{coherentCVs}} - \frac{f(fix\ incoherent\ cue\ value)}{n_{incoherentCVs}}$. CAS values larger than zero indicate that participants were on average more likely to fixate coherent than incoherent cue values and are in line with the predictions of the coherence attention effect. A CAS value of 1 implied perfect prediction, while negative values imply hypothesis incongruent allocation of attention.

Procedure. The experiment was conducted in accordance with the ethical standards of the American Psychological Association (APA). In the experiment, participants were instructed to imagine playing a hypothetical stock-market game. In this game, they had to decide which stock was going to be more successful in the future. Participants were tested in single sessions. After arriving in the lab, participants gave their informed consent, generated an individual pseudonymization code, and answered

[8] For the calculation of the AAS, only trials were included in which the first fixation in the decision phase was on a formerly concealed cue value. This was the case in 56.1% of all trials.

questions about their handedness.[9] Participants were given paper instructions for the experiment describing the details of the stock-market game.[10] Specifically, their task in each trial was as follows (see also Figure 2): After a fixation cross was presented, they had the opportunity to familiarize themselves with the current cue pattern with still concealed cue values. Participants then rated option attractiveness in a self-paced manner. After giving their ratings, another fixation cross was presented followed by the cue pattern with now revealed cue values. Participants' task was to decide between the stocks in a self-paced manner.

After reading the (paper) instructions, participants were placed in front of the eye tracker. The chair and the head rest were adjusted to be comfortable for the participant. Following a short introduction and practice trials, the position of the eyes was controlled and the eye tracker was calibrated. Then, the experiment, which was programmed using *OpenSesame* (Mathôt et al., 2012), was started. After half of the trials (64 trials), participants could take a break during which they received feedback on how much money they had earned so far. The feedback was implemented to keep participants motivated for the task. After the break, the eye tracker was calibrated one more time before continuing with the second half of the experiment.

After the task, participants indicated the validities of the experts in the stock-market game to assure that they remembered them correctly during the task. They further answered demographic questions, particularly about their eye sight (whether they wore glasses/contacts, what their diopters were, the color of their eyes). After the demographic questionnaire, subjects worked on a further experiment that is unrelated to our research question. Afterwards, participants were debriefed and thanked for their participation.

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[9] Participants' handedness was collected for a subsequent experiment for which data were collected following our study.

[10] All instructions and experimental files are uploaded to OSF, https://osf.io/j7v9a/?view_only=509578b5215e4115a46cf923cf2b7f40

Results

The data and analyses scripts of this experiment can be found on OSF, https://osf.io/j7v9a/?view_only=509578b5215e4115a46cf923cf2b7f40. Supplemental, exploratory analyses are reported in the online supplement.[11]

Attraction Attention Effect (H1). We hypothesized that the attraction search effect generalizes to attention. Hence, participants should be more likely to fixate newly revealed information for the currently attractive option than for the currently unattractive option as determined by iCodes. To test this attraction attention effect (H1), we ran a one-sample t test against zero with the attraction attention score (AAS) as dependent variable based on the fixations in the decision phase of the experiment. A positive AAS was in line with the predicted attraction attention effect. The AAS was on average larger than 0, $M = 0.32$ ($SE = 0.03$), $t(56) = 12.40$, $p < .001$, tested one-sidedly, Cohen's $d = 1.64$.[12] Therefore, participants showed a strong tendency to fixate information on the attractive option first.

Coherence Attention Effect (H2). One of the core predictions of iCodes is that coherent information in the decision phase should be fixated more often than incoherent information. To test this coherence attention effect (H2), we calculated the coherence attention score (CAS) based on the fixations on all revealed cues in the decision phase of the experiment. An on average positive CAS would indicate that participants were more likely to attend to coherent information. Indeed, the average CAS was significantly larger than zero, $M = 0.03$ ($SE = 0.002$), $t(56) = 14.89$, $p < .001$, tested one-sidedly, Cohen's $d = 1.97$, supporting Hypothesis 2.

In a follow-up analysis, we analyzed only trials in which the newly revealed cue

[11] In both experiments, we deviated from some of the planned analyses reported in the pre-data reports, partly due to methodological concerns, partly for improving the overall comprehensibility. For a detailed account of and explanations for the deviations, see the online supplement.

[12] For this analysis, we included only trials in which the newly revealed information was fixated first. An analysis calculating the attraction attention score on all trials, replicated the result, $M = 0.36$ ($SE = 0.02$), $t(56) = 16.18$, $p < .001$, Cohen's $d = 2.14$. Thus, in the decision phase participants were more likely to fixate any information describing the previously attractive option in the rating phase.

values in the decision phase made the same prediction (i.e., both positive or both negative). In these trials, cues do not discriminate between options and, therefore, can be ignored according to most decision strategies. According to iCodes, the coherent cue value should be fixated more than the incoherent cue value (e.g., the "+" for an attractive option should be fixated more than the "+" for the less attractive option, although both come from the same cue). We tested this coherence attention effect for non-discriminating cue values (H2a) by calculating the CAS for fixations on the newly revealed, non-discriminating cue values only. According to a one-sample t test against zero, participants were more likely to fixate the coherent, indiscriminatory cue value than the incoherent, as indicated by a positive CAS, $M = 0.02$ ($SE = 0.007$), $t(56) = 3.27$, $p = .001$, tested one-sidedly, Cohen's $d = 0.43$.

Late Coherence Effect (H3). The prediction of the late coherence effect entails that the coherence of information influences fixation behavior more towards the end of a trial, while in the beginning of a trial cues' validities are more predictive of which information will be fixated (H3). To test this predictions, we conducted two analyses of the gaze data from the rating phase of the experiment.As in the rating phase the cue values from one cue were still concealed and concealed cue values are neither coherent nor incoherent, we did not include fixations on the concealed cue values in the following analysis. In the first analysis, we tested whether the tendency to fixate coherent information increased over the course of a trial. As a dependent variable for this analysis, we calculated a *coherence preference score* (CPS).[13] This score represents the relative frequency of fixating coherent information minus the expected probability of fixating coherent information in each trial if fixations would be equally distributed between cue values (i.e., random), $CPS = f(fix_{coherent}) - \frac{n_{coherentCVs}}{total\ n_{CVs}}$. If participants tended to fixate coherent information more frequently than incoherent information, the average CPS should be positive. We tested the effect of time in each

[13] The analyses for the late coherence effect deviate from those pre-registered in the pre-data report. For a detailed account and explanations for deviations from the pre-data report, see the online supplement.

trial on the CPS by binning the fixations into the first half and the second half of the rating phase and running a paired t test. If the tendency to fixate coherent information increased over the course of the rating phase, we would expect a higher CPS in the second time bin than in the first time bin. There was no significant effect of time bin on the CPS, $M_{FirstBin} = 0.02$ ($SE = 0.006$), $M_{SecondBin} = 0.01$ ($SE = 0.004$), $t(56) = 1.58$, $p = 0.120$, tested two-sidedly, Cohen's $d = 0.21$, that is, the data did not support the predicted change in the probability of fixating coherent information between the first and the second half of a trial (H3). The average coherence preference score, however, was significantly larger than zero across time bins, $M_{CPS} = 0.02$ ($SE = 0.004$), $t(56) = 4.68$, $p < .001$, tested two-sidedly, Cohen's $d = 0.62$, pointing to an overall preference to fixate coherent information (in line with the results for the coherence attention effect reported above for H2).

In a second step, we tested whether the validity influence on fixations decreased over the course of a trial (H3). We again analyzed fixations from the rating phase of the experiment but, in contrast to the analysis from above, we also included fixations on concealed cue values. For this purpose, we calculated an additional index that represents the difference of the frequency of fixating a specific cue in the first bin minus the frequency of fixating this cue in the second bin in each trial (fixation difference score, FDS), $FDS = p(fix_{cue}|first\ bin) - p(fix_{cue}|second\ bin)$. Thus, when a cue is fixated more in the first half of a trial than in the second half of the trial, this index is positive while it is negative when a cue is fixated less often in the first than in the second half of a trial. To analyze whether participants were more likely to fixate valid information compared to invalid information in the beginning of a trial, we ran a within-subjects ANOVA with the validity of a cue (.60 vs. .70 vs. .80 vs. .90) as predictor and the calculated index as dependent variable and Greenhouse-Geisser corrected degrees of freedom.[14] If the late coherence effect provides an adequate description of the fixation behavior, we would expect linearly increasing FDS from the

[14] Note, as coherence was not explicitly manipulated in this experiment, validity and coherence were potentially confounded in this index.

least valid to the most valid cues. The results revealed a main effect of cue validity, $F(2.26, 126.81) = 116.82$, $p < .001$, generalized $\eta^2 = .676$. We ran post-hoc polynomial contrasts to test whether the expected linear trend was supported. The results revealed a significant linear trend in the FDS, $b = 0.99$, $t(168) = 17.86$, $p < .001$ and a significant cubic trend, $b = -0.30$, $t(168) = -5.32$, $p < .001$ (see Figure 3 for a visualization of the interaction pattern). The results therefore supported the prediction of iCodes that validity influenced fixation behavior more in the beginning of a trial than towards the end of trial and that the frequency of fixating cues increased linearly with their validity.

Gaze Cascade Effect (H4). To investigate whether participants attended to the subsequently chosen option more towards the end of a trial (H4), we ran a mixed Logistic regression with the probability of fixating the left option as dependent variable (1 = fixated left option, 0 = fixated right option). We included the chosen option (left $= +1$ vs. right $= -1$, effect-coded) and time bins (first half $= +1$ vs. second half $= -1$, effect-coded) as predictors. Additionally, we added the z-standardized trial number as predictor to account for changes in the fixation behavior across the experiment and random intercepts for participants to account for inter-individual variability.

The results of this mixed model showed a significant effect of bins, $OR = 1.06$, $z = 5.24$, $p = .001$, indicating that participants were more likely to fixate the left option in the first than in the second half of a trial. There was also a main effect of the subsequently chosen option, $OR = 1.57$, $z = 41.83$, $p < .001$, indicating that overall participants were more likely to fixate the left option given the left option was chosen later on. Most importantly, there was a significant interaction of bins and the chosen option, $OR = 0.97$, $z = -3.14$, $p = .002$, supporting the main prediction of the gaze cascade effect, namely that participants were more likely to fixate their chosen option towards the end of trial (see also Figure 4).

Discussion

The results of Experiment 1 showed that the attraction search effect also generalizes to potentially more automatic visual search: Participants were more likely to fixate newly revealed information describing the attractive option first (H1). This finding supported the role of option attractiveness in information search and substantiated that iCodes information-search predictions are not limited to more deliberate and active information search as implemented for example in standard information-board paradigms (e.g., Payne et al., 1988). In addition, participants were more likely to fixate coherent compared to incoherent information during the decision phase of the experiment (H2), and this pattern also held up for the non-discriminating - and, therefore, irrelevant - newly revealed cue values (H2a).

There was also support for the change in the fixation patterns based on the validity of cues, in that participants' fixations were more influenced by cues' validities in the beginning of the trial than in the end of the trial. The polynomial post-hoc contrasts revealed a cubic trend of the fixations in addition to the predicted linear trend. The cubic trend was likely due to the tabular design of the screen in which cues with validities of .70 and .80 were presented closer to the center of the screen and the fixation cross than the cues with validities of .60 and .90. As participants were presented with a fixation cross before each trial, it is plausible that the cubic trend was an artifact of the proximity of the two mid-valid cues to the fixation cross. We did not observe an increase in the probability of fixating coherent information over the course of a trial (H3). The influence of coherence on attention allocation seemed to be constant across the trial and there was no indication for a late coherence effect. An explanation for the lack of evidence for the late coherence effect could lie in the experimental design: We chose the two-stage design that asked for option-attractiveness ratings in the first stage and revealed new cue values in the second stage to increase the chances to observe an attraction attention effect. Yet, this two-stage design might have decreased the chances to find evidence for the late coherence effect. For example, it could be that the role of option attractiveness in the information-integration process is different depending on if the task was to rate option attractiveness rather than to decide for one of the options. Further, as we based our analyses on the rating phase of the experiment, we had to exclude fixations on the AOIs of concealed cue values as these could not be defined as coherent or incoherent resulting in a loss of information and, thus, reduced power to find the predicted effect.

The gaze pattern predicted by the gaze cascade effect was supported by the data (H4). Yet, the effect of the gaze cascade effect was relatively small and there was also a strong main effect of preferentially fixating the subsequently chosen option irrespective of the time point during the experiment. Similar to the late coherence effect, the gaze cascade effect might have been disrupted due to the two stage design as most of the information has already been integrated before the fixations occurred in the decision phase which we analyzed for the gaze cascade effect. Thus, the main goal for Experiment 2 was to adequately investigate the time course of the coherence influence on attention allocation by utilizing a one-stage experimental design. Further, we strove to eliminate distance-based and reading-direction artefacts by optimizing the visual display of the information.

Experiment 2

Experiment 1 supported the prediction that participants preferentially searched for new information describing the attractive option first (H1). In Experiment 2, we aimed to investigate the coherence attention effect (H2) as well as the late coherence effect (H3) and the gaze cascade effect (H4) in more detail using a modified design. The coherence attention effect states that participants should be more likely to attend to coherent compared to incoherent information. The late coherence effect states further that this tendency should increase towards the end of the trial, while, in the beginning of a trial, attention allocation should be mainly influenced by the validity of information. According to the gaze cascade effect, participants should increasingly fixate the option they subsequently choose over the course of a trial.

Although the coherence attention effect was already supported in the first experiment, there was no clear support for the late coherence effect. While validity influenced fixations mainly in the beginning of a trial (in line with the late coherence effect), the predicted increase of the coherence influence on fixation towards the end of a trial was not supported by the results. One reason for not finding the predicted effect might have been the two-stage design of the first experiment, as it split the decision process artificially in two. Therefore, it was difficult to derive for which phase the time-course predictions of iCodes should apply. Another reason could have been the presentation of the decision task in a table: As cue information was ordered and not equidistant from the screen, confounds due to cue position and reading direction could have affected fixation behavior. Thus, in the second experiment we utilized a circular presentation of the information (cf. Fiedler & Glöckner, 2012), varied the order of the cues between trials, and presented all the information openly at once. With these changes, we aimed to prevent confounds of the presentation format and reading direction. Furthermore, we aimed to record fixations during the entire information-integration and decision process by presenting all information at once.

In Experiment 2, we additionally designed new cue-value patterns that manipulated the coherence of the presented information. For this purpose, we constructed two versions of each cue pattern. The difference between the two versions was that two out of four cues changed which option they supported. In Version a, these two changing cues supported Option A and in Version b, the same cues supported Option B (see the cues with a white background in Table 2). The remaining two cues did not differ between the versions: One of these unchanging (i.e., constant) cues always supported Option A, while the other always supported Option B (see the cues with a grey background in Table 2). Due to the two changing cues, however, the relative coherence of the two constant cues was manipulated: The constant cue that supports Option A is coherent in Version a of the cue patterns, as the changing cues also support Option A. The constant cue that supports Option B is coherent in Version b, as the changing cues also support Option B. As iCodes predicts that coherent cues are fixated relatively more often than incoherent cues, it predicts that the relative frequency of fixations on the constant cues should differ between the pattern versions, as the coherence of these cues differs.

Note, that this manipulation of coherence is not independent of the cues' validity.

As iCodes predicts that not only cues' coherence but also their validity is a determinant of attention allocation during the decision process, we only expect a relative change of the number of fixations on the constant cues between versions. Specifically, if participants' behavior was in line with the late coherence effect, we would expect that in the beginning of a trial the probability of fixating the constant cues does not differ between the two cue-pattern versions in that in both versions the more valid, constant cue is fixated more than the less valid constant cue. Towards the end of a trial, we expect to find an effect of the cue-pattern versions such that the constant cue supporting Option B should be fixated relatively more in Version b in which Option B is more attractive. On the other hand, the constant cue supporting Option A should be fixated relatively more in Version a than in Version b in the second half of the trial. In addition to testing the late coherence effect (H3) based on the newly designed cue-value patterns, we also tested the coherence attention effect (H2) and the gaze cascade effect (H4) in Experiment 2. Finally, we also tested the attraction attention effect (H1), adapted to a one-stage experimental design without concealed cue values. Just as for Experiment 1, the study was pre-registered and a pre-data report detailing the hypotheses, methods, and planned analyses for this experiment is available at: https://osf.io/ykjqr/?view_only=c3c25c7809ae4638aa8d5a9702ad2dcf.

Methods

Design and Participants. We manipulated the coherence of cues within-subjects (more valid, constant cue coherent - Version b vs. incoherent - Version a). Further, we compared the fixation behavior in the first half to the second half of the trial (time bin: first vs. second half), resulting in a 2x2 within-subjects design.

In Experiment 2, we changed the task design compared to the pilot experiment and Experiment 1. With these changes, we expected to find at least a medium-sized interaction effect of $f = 0.25$ for the interaction of time bins and cue-pattern version in a 2x2-within-subjects repeated measures ANOVA. With $\alpha = \beta = 0.05$, $r_{betweenMeasures} = .5$, Nonsphericity correction $\epsilon = 1$, the resulting sample size was

$N = 54$ (cf. Faul et al., 2007).

We collected data of $N = 50$ participants (34 female, $M_{age} = 25.46$, range: 18-35).[15] Just as in Experiment 1, participants received a 5 Euro show-up fee and were able to earn extra money depending on their choices. For every correct decision, participants received 6 Cents allowing a maximum total of 8.64 Euro on top of the show-up fee (average total payoff $M_{payoff} = 13.22$ Euros, approx. USD 16.03, $SD_{payoff} = 0.54$, range: $11.50 - 13.70$ Euros).

Materials. We created two versions of six cue-value patterns for a hypothetical stock-market game that explicitly manipulated the coherence of cue values for Experiment 2. The validities of the cues in these patterns were .70, .68, .62, and .60. The cue-values of two cues always remained the same between the two versions and always discriminated between options (the grey cells in Table 2). In Patterns 1 - 3, Cues 3 and 4 were held constant, while in Patterns 4 - 6, Cues 1 and 2 were held constant. The experimental manipulation via the cue-pattern versions changes the coherence of the constant cue values: In Version a, the bottom, constant cue was coherent as it supported Option A, while in Version b, the top, constant cue was coherent as it supported Option B. Thus, we expected relatively more fixations for the constant cues (grey cells in Table 2), that is, Cues 2 and 4 in Pattern Version a and Cues 1 and 3 in Pattern Version b.

The cue patterns were shown on a circular display such that all cue values were equidistant to the center of the screen (see Figure 5). In contrast to Experiment 1, we also changed the ordering of cues. The cues were ascending in their validities for one option and descending for the other option. This presentation format was used to avoid confounding cue validity with reading direction (i.e., the most valid cue is always shown in the top-left of the screen). To make the validity information even more accessible and to facilitate cue-wise comparisons, we assigned colors to each cue and each validity. We

[15] Data collection was cut short, as experimental labs at the University of Cologne were closed due to the Covid-19 pandemic. With a sample of $N = 50$, the power to find a medium sized interaction effect of $f = 0.25$ was $1 - \beta = 0.93$.

selected four colors from the HSL colorspace (cf. Ibraheem et al., 2012) with luminance and saturation of 50% and equidistant hues. Which option was presented with ascending/descending cue values was counter-balanced across the experiment. Additionally, we counterbalanced whether Option A was displayed on the left or on the right side of the screen. The order of trials was pseudo-randomized, such that the same combination of cue-value patterns and counter-balanced factors was not repeated before not at least three different patterns were shown in between. In total, each participant made decisions in 144 trials (6 patterns x 2 versions x 2 validity orders x 2 screen sides x 3 repetitions).

Measures. As in Experiment 1, we measured which option subjects chose and whether their choice was correct. Data on eye movements were collected with the same system as in Experiment 1. As we were again interested in what information participants fixated, we defined eight AOIs around the location of the cue values on the screen ($\pm$ 75 pixels from the cue value center). Our main dependent variables were which AOIs were fixated and how often specific AOIs were fixated.

We again calculated eye-tracking indices for each subject to test our hypotheses. Most notably, we calculated an attention difference score (ADS) with the purpose to capture changes in fixation behavior due to the change of cues' coherence. The ADS represents the difference between the relative frequencies of fixations on the constant cues (i.e., Cue 3 and 4 in Pattern 1-3 and Cue 1 and 2 in Pattern 4-6); $ADS = f(fixating\ Cue\ 1\ or\ 3) - f(fixating\ Cue\ 2\ or\ 4)$. Positive ADS values in Version a indicated that the incoherent, constant cue was fixated more, while in Version b positive ADS values indicated that the coherent, constant cue was fixated more. With regard to the late coherence effect, we would expect that, in the beginning of a trial, the ADS scores are positive independent of pattern version, as the top, constant cue (Cue 1 or 3) should be fixated more than the bottom, constant cue (Cue 2 or 4) irrespective of its coherence. Towards the end of a trial, we expect the ADS to be larger in Version b than in Version a, as the coherent, constant cue should be fixated more (Cue1 or 3 in Pattern Version a, Cue 2 or 4 in Pattern Version b).

In addition to the ADS, we also calculated the attraction attention score (AAS) similar to the one in Experiment 1. Due to the change in experimental design, the AAS in Experiment 2 relied on the first two fixations in each trial and was calculated as follows: $AAS = p(switch\ option\ second\ fixation|first\ fixation\ on\ -) - p(switch\ option\ second\ fixation|first\ fixation\ on\ +)$. Positive AAS values were again in line with iCodes's predictions. Lastly, we also calculated the same coherence attention score (CAS) in Experiment 2 as in Experiment 1.

Procedure. The experiment was conducted in accordance with the ethical standards of the American Psychological Association (APA). The general task and procedure was the same as in Experiment 1, except for the following differences. Instead of a two-stage design, all information was presented to the participants at once and they had to directly decide between the two stocks. To ensure that participants were aware of the order of validities in the current trial and to avoid the need to scan the whole screen, the order of the validities in the subsequent trial was shown in the center around the fixation cross 200 ms after the fixation cross was initially displayed. After a total of 1700 ms the decision task was presented and participants indicate which stock they wanted to buy by pressing keys on the keyboard in a self-paced manner (see Figure 5). Again, after half of the trials (72 trials), participants could take a short break and received feedback on their current earnings. After finishing the experiment, participants again started a second, unrelated eye-tracking experiment.

Results

The data and analysis scripts of this experiment can be found on OSF, https://osf.io/ykjqr/?view_only=c3c25c7809ae4638aa8d5a9702ad2dcf. Supplemental, exploratory analyses mentioned in the pre-data report can be found in the online supplement.

Attraction Attention Effect (H1). In a first step, we analyzed whether participants tended to continue their search on the currently attractive option given the first information they looked at was positive (H1). For this purpose, we calculated the attraction attention score (AAS) across trials. We ran a one sample t test against zero with the AAS as dependent variable that indicated that the AAS was on average larger than zero, $M = 0.08$ ($SE = 0.02$), $t(49) = 4.90$, $p < .001$, tested one-sidedly, Cohen's $d = 0.69$. Thus, participants' second fixations were more likely to be on the same option as the first, if the first fixated AOI contained a positive cue value as compared to a negative cue value, which was in line with the attraction attention effect.

Coherence Attention Effect (H2). We also tested whether the attention difference score (ADS) was higher in Version b of the cue pattern than in Version a. A higher ADS in Version b would indicate that participants were overall more likely to fixate the coherent, constant cue in line with the coherence attention effect (H2). We ran a paired t test with the ADS as dependent variable and pattern version as independent variable. As predicted, the average ADS is higher in Pattern Version b than in Pattern Version a, $M_a = 0.06$ ($SE = 0.02$), $M_b = 0.09$ ($SE = 0.02$), $t(49) = 2.75$, $p = .004$, tested one-sidedly, Cohen's $d = 0.39$, and both average ADS are above 0 ($ts > 3.68$, $ps < .002$). Thus, participants generally fixated more valid constant cues and also preferentially fixated the more coherent cue.

In a second analysis, we replicated the analysis reported for Experiment 1 by calculating the coherence attention score (CAS) across all cue patterns. In a one-sample t test with the CAS as dependent variable, we found support that the CAS on average was larger than zero, $M = 0.01$ ($SE = 0.002$), $t(49) = 7.70$, $p < .001$, tested one-sidedly, Cohen's $d = 1.09$. This again supported the hypothesis that participants fixated coherent information more than incoherent information.

Late Coherence Effect (H3). The late coherence effect states that in the beginning of the trial the validity of a cue should be the main determinant of fixation behavior, while towards the end of a trial the coherence of a cue value should gain more influence on fixation behavior (H3). To test this hypothesis in Experiment 2, we ran a 2x2 within-subjects ANOVA with the predictors bins (first vs. second) and pattern version (a vs. b) and the attention difference score (ADS) as dependent variable. We would expect that the ADS does not differ between pattern versions in the first bin, as the difference in coherence of the constant cues should not yet influence fixation behavior. In the second half of the trial on the other hand we would expect an effect of pattern version. Specifically, we expected that the ADS is larger in Version b than in Version a, indicating that the coherent cue was fixated relatively more often in both versions. The results of the ANOVA showed no main effect of bins, $F(1, 49) = 0.13$, $p = .720$, generalized $\eta^2 < .001$, but a main effect of pattern version, $F(1, 49) = 5.54$, $p = .023$, generalized $\eta^2 = .007$, indicating that the mean ADS was larger in Version b ($M_b = 0.08$) than in Version a ($M_a = 0.06$). This main effect of pattern version was in line with the results reported for the coherence attention effect (H2). Yet, the predicted interaction was not significant, $F(1, 49) = 2.37$, $p = .130$, generalized $\eta^2 = .006$. When plotting the results, it appeared, nonetheless, that there was a larger difference of the ADS in the second time bin (see Figure 6). Analyzing the simple main effects of pattern version, the version effect was not significant in the first bin, $t(90.6) = -0.17$, $p = .864$, but significant and in the predicted direction in the second bin, $t(90.6) = -2.64$, $p = .010$.

Gaze Cascade Effect (H4). We again analyzed whether participants increasingly fixated the option they subsequently chose across a trial (H4). For this purpose, we ran a mixed Logistic regression with two time bins (first = +1 vs. second = -1, effect-coded) and whether participants chose the left (= +1) vs. right (= -1) option (effect-coded) as predictors. The dependent variable was whether participants fixated the left option (1) or the right option (0). To account for changes in fixation behavior over the experiment, we included the z-standardized trial number as predictor and we included random intercepts for participants to account for inter-individual variability. The results showed that participants tended to fixate the left option more in the first half of the trial than the second half of the trial, $OR = 1.07$, $z = 9.99$, $p < .001$, as well as that they tended to fixate the left option more often if they chose it subsequently, $OR = 1.23$, $z = 28.82$, $p < .001$. The Gaze Cascade Effect prediction was supported by a significant interaction of time bins and the chosen option, $OR = 0.92$, $z = -11.45$, $p < .001$ that showed an increase of fixations on the chosen option (see

Figure 7).

Discussion

In Experiment 2, we replicated the attraction attention effect from the previous study (H1). Participants preferentially fixated information for the same option if they fixated a positive cue value for this option first. The effect size of the attraction attention effect was considerably smaller in Experiment 2 compared to Experiment 1. A difference between the two experiments was that the measurement of the attraction attention effect was much cleaner in Experiment 1 than in Experiment 2: In Experiment 1, we only considered the first fixations on the two newly revealed and equally valid cue values. Thus, there was no interference from validity or an initial scanning of the presented information. In Experiment 2, on the other hand, attention allocation was less guided by the experimental design which might explain the reduced effect size. This explanation would be in line with findings that the size of the attraction search effect decreased in less structured decision tasks (cf. Scharf et al., 2019).

There was also support for the prediction that participants fixated coherent information more than incoherent information (coherence attention effect, H2). This preference for coherent information was found for the constant, coherent cue values as a result of the experimental manipulation as well as for all cue values in a trial, replicating the results from Experiment 1. The coherence attention effect due to pattern version was a substantially smaller effect than the coherence attention effect across the whole cue pattern. One explanation for this difference lies in the nature of the coherence manipulation: In Version a, the coherent cue is less valid than the coherent cue in Version b. This difference in validity was still reflected in the attention difference score, our main dependent variable, as it is the difference of the relative frequency of fixations on the more and the less valid cue. Yet, the coherence attention score aggregated the fixations on coherent cue values across differing validities. As people generally show a stronger validity influence on their information search, which is also incorporated into the model (cf. Jekel et al., 2018), it is unsurprising that the analysis aggregating across validities shows a larger effect of coherent on participants' fixation behavior. Finding evidence for a coherence influence on attention even when explicitly accounting for validity differences, however, further supports the importance of coherence in the information-search process beyond the validity influence.

The main focus of this experiment was to test the late coherence effect (H3). While there was a main effect of pattern version in line with the results of the coherence attention effect and the results of Experiment1, the predicted interaction with time was not significant. Yet, post-hoc simple main effects showed the predicted pattern: The attention difference score (ADS) was positive and did not differ between pattern versions in the first half of a trial. In the second half of a trial, the difference of the ADS between the pattern versions was significant, in that the ADS was higher for Pattern Version b than for Pattern Version a. These results complied with the prediction of the LCE descriptively such that participants preferentially fixated coherent information towards the end of the trial. Nonetheless, this result should be, if at all, interpreted only with caution, as the predicted interaction in the ANOVA was non-significant. Thus, we replicated the main effect of the coherence influence from Experiment 1 but did not find (strong) support for the time component of this coherence influence.

Last but not least, we again found support for the prediction of the gaze cascade effect in that participants' probability to fixate their subsequently chosen option increased over the course of a trial. Compared to the results of Experiment 1, the gaze cascade effect was larger in the second experiment. This difference in effect size is likely due to observing the gaze cascade effect in a one-stage experimental design in Experiment 2 compared to the two-stage experimental design in Experiment 1: Most of the information integration in Experiment 1 likely already took place during the rating phase and, thus, the predicted pattern of fixations might have been diluted in the decision phase, for which we analyzed the gaze cascade effect. In Experiment 2, on the other hand, all information was presented at once and, thus, we could observe the whole information-integration process leading up to the decision.

General Discussion

In this article, we derived and tested predictions for attention allocation by iCodes, a new, coherence-based model for decision making and information search (Jekel et al., 2018). Specifically, we tested whether participants would (visually) search for new information describing the attractive option first (attraction attention effect, H1), whether they preferentially fixated coherent information (coherence attention effect, H2), whether this preference for coherent information increased over the course of a trial (late coherence effect, H3), and whether they fixated the option they subsequently chose with increasing probability over a trial (gaze cascade effect, H4). For this purpose, we ran two experiments utilizing a hypothetical stock-market game while measuring participants' attention allocation. In the first experiment, we focused on finding support for the attraction attention effect by utilizing a two-stage experimental design: In the first stage, participants were presented with a decision situation with one concealed cue, that was then revealed in the second stage allowing us to observe which new information participants attended to first. In the second experiment we focused on finding support for the late coherence effect by explicitly manipulating the coherence of information in a one-stage hypothetical stock-market game.

The results of both experiments supported the prediction that participants preferentially fixated new information describing the attractive option first, replicating the findings for active information search by Jekel et al. (2018). Further, both experiments showed that participants indeed fixated coherent information more than incoherent information, supporting the most central prediction of iCodes. Participants' tendency to fixate their subsequently chosen option increased over the course of a trial in Experiment 1 as well as in Experiment 2, providing support for the gaze cascade effect. There was, however, no strong support for the prediction that the influence of coherence on fixation behavior increases over the course of the trial in both experiments. While the results of both experiments supported a stronger validity influence on fixations in the beginning of the trial, both did not strongly support a change in the coherence influence over the trial.

iCodes as a theory of coherence-based attention allocation

The results from our two experiments support the notion that the coherence of information is a relevant top-down influence factor for attention allocation and (more) automatic visual search. By predicting this coherence influence, iCodes establishes itself as a noteworthy contender for describing the relation between attention, information search and choice. We are not aware of other models in decision making that predict the influence of coherence on attention (without making auxiliary assumptions). In addition, iCodes makes precise predictions about the sequence of fixations with the attraction attention effect (H1) such that participants should fixate information that describes the attractive option first. The attraction attention effect was shown in Experiment 1 that utilized a two-stage design to cleanly observe participants' attention to new information but also in Experiment 2 which did not guide participants' information search explicitly. A recent extension of the attentional drift diffusion model (aDDM, Krajbich et al., 2010) predicts that options with higher subjective values are fixated more often (Gluth et al., 2020), a gaze pattern that is similar to the prediction of the attraction attention effect. Yet, the extended aDDM makes this prediction only on the option level, while iCodes inherently predicts fixations on the cue-value level. In addition to the precise and a priori prediction about fixation sequences, iCodes is at a theoretical advantage compared to the aDDM that generally assumes a stochastic fixation process and uses the empirically observed fixation pattern in modelling.

One caveat is the lack of clear support for the time-course prediction of the late coherence effect (H3). While participants were influenced more by information's validity in the beginning rather than the end of a trial, we did not observe a clear increase in the coherence influence on attention towards the end of a trial. Even though it is too early to conclude that this lack of support invalidates the assumed information-search process, it gives reason to reevaluate the time-course prediction and the strength of the coherence influence overall.

Showing that participants increasingly fixated the option they finally chose, did not only support iCodes and its prediction of the gaze cascade effect (Shimojo et al.,

2003) but also the evidence-accumulation models that also predict this gaze pattern (Busemeyer & Johnson, 2004; Krajbich et al., 2010), at least for the very last fixation. The generality of the gaze cascade effect has been recently challenged by Sepulveda et al. (2020) who showed that changing the framing of a decision task from choosing to rejecting an option reversed the gaze pattern such that the subsequently rejected option was fixated more towards the end of a trial. While this result cannot be reconciled with the current implementation of iCodes, the model can be easily adapted to capture this pattern: Currently, the option nodes are thought to represent an untransformed representation of the options at hand. Yet, the option nodes could also be thought of as representing the current hypothesis about an option that is being tested (such as "Option A is the better/worse option" and "Option B is the better/worse option", cf. Holyoak & Simon, 1999). This re-conceptualization of the option nodes would make the inferior option the preferred option under a rejection frame. Interestingly, this would also lead to the prediction that participants should fixate new information on the currently inferior option first, a prediction that can be easily tested and, thus, be used to evaluate the suggested re-conceptualization of the option nodes.

Limitations and Future Directions

Our experiments did not manage to provide convincing evidence for an increase of the coherence influence over the course of a decision trial. The results of the second experiment give reason to believe that the late coherence effect (H3) might be much smaller than a priori expected and, thus, our achieved power was insufficient to find the predicted interaction effect. Given the small effect, more extensive simulations might be necessary to identify conditions under which the LCE should be more or less pronounced. On basis of such simulations, future research could investigate the boundary conditions of the LCE.

As our experiments were the first to investigate coherence-based information search by utilizing eye tracking, we aimed at keeping our analyses as simple as possible by aggregating across manipulations and trials. In addition, to best communicate our core results, we focused on the analyses of our main hypotheses instead of additionally testing potential moderators. However, other ways of data analysis, such as multilevel modeling of single trials or the assessment of potential moderators might be an interesting route for future research. For example, iCodes predicts that the gaze cascade effect should be moderated by the amount of coherent information on the chosen option. One could design an experiment that investigates this predicted interaction of the coherence of cue values, choice, and the temporal dynamics of fixation behavior by explicitly manipulating the number of coherent cue values describing the attractive option. To gain preliminary insights into the influence of potential moderators in our data, we conducted some exploratory analyses that are presented in the online supplement. These results may serve as a guidance to design future experiments.

Following the same reasoning as above, we did not fit the free parameters in iCodes to the eye-tracking data of the two experiments.[16] In future research, one could benefit from the full potential of iCodes by explicitly modelling its predictions for attention allocation. For example, one could compare aDDM (Krajbich et al., 2010) and iCodes directly by creating a paradigm that allows to fit both models to the same data and compare the respective model fits. Further, it would be interesting to test whether the γ parameter that models individual differences in the relative strength of the coherence influence on information search within iCodes (cf. Scharf et al., 2021) could explain differences in fixation behavior as well.

One strength of iCodes is that it allows to model the influence of bottom-up influences on attention, such as visual salience on information search. Bröder et al. (2021) showed in an information-board setting that, for example, salient, concealed cue values were more likely to be opened and that any salient information on an option increased the probability to search for more information on said option. In the current experiments, we did not manipulate visual salience of information. In future research, one should test whether the behavioral findings for the interplay of coherence and

[16] We conducted some preliminary analyses based on fixed parameters that are reported in the online supplement.

salience generalize to gaze data and whether an extension of iCodes that explicitly models the influence of cue salience is able to adequately describe these data.

Our results highlight the benefits of investigating gaze behavior when evaluating decision-making theories. Doing so allowed more detailed testing of iCodes's predictions and provided important insights concerning the underlying information-search process that takes place during a decision. One important advantage of utilizing eye tracking is the possibility to observe information acquisition in an unobtrusive way without the need for information boards, that have been shown to change the way information was integrated (Glöckner & Betsch, 2008b). Thus, eye tracking allows the investigation of information search in less constrained and more naturalistic settings. An interesting direction for future research would, therefore, be to utilize eye tracking for evaluating the information-search predictions by different decision-making models across paradigms.

Conclusion

In previous work (e.g., Orquin & Mueller Loose, 2013), the importance to develop and test integrative models for decision making, attention, and information search has been highlighted. With this article, we contribute to closing this gap in the research literature by providing a detailed test of predictions derived from the integrated model for coherence based decision making and search (iCodes). The results show that information-search processes are more complex than usually assumed such that coherence plays an important role in determining search. We show that the attraction search effect originally observed in tasks for active and deliberate information search generalizes to more automatic and visual search and attention allocation. Furthermore, a more general influence of coherence on attention allocation could be confirmed in the analyses. The presented findings provide a starting point for theory development and critical model comparisons of models that describe various aspects of the decision process and take into account the complex interplay of attention, information search, and information integration in decision making.

References

Atalay, A. S., Bodur, H. O., & Rasolofoarison, D. (2012). Shining in the center: Central gaze cascade effect on product choice. *Journal of Consumer Research*, *39*(4), 848–866. https://doi.org/10.1086/665984

Bialkova, S., & van Trijp, H. C. M. (2011). An efficient methodology for assessing attention to and effect of nutrition information displayed front-of-pack. *Food Quality and Preference*, *22*(6), 592–601. https://doi.org/10.1016/j.foodqual.2011.03.010

Bröder, A., Scharf, S. E., Jekel, M., Glöckner, A., & Franke, N. (2021). *Salience effects in information acquisition: No evidence for a top-down coherence influence* (Manuscript submitted for publication).

Busemeyer, J. R., & Johnson, J. G. (2004). Computational models of decision making. In D. J. Koehler & N. Harvey (Eds.), *Blackwell Handbook of Judgment and Decision Making* (pp. 133–154). Blackwell Publishing Ltd. https://doi.org/10.1002/9780470752937.ch7

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Cognitive Science*, *3*, 335. https://doi.org/10.3389/fpsyg.2012.00335

Fisher, G. (2017). An attentional drift diffusion model over binary-attribute choice. *Cognition*, *168*, 34–45. https://doi.org/10.1016/j.cognition.2017.06.007

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological review*, *103*(4), 650–669. https://doi.org/10.1037/0033-295X.103.4.650

Glaholt, M. G., & Reingold, E. M. (2009). Stimulus exposure and gaze bias: A further test of the gaze cascade model. *Attention, Perception, & Psychophysics*, *71*(3), 445–450. https://doi.org/10.3758/APP.71.3.445

Glaholt, M. G., & Reingold, E. M. (2011). Eye movement monitoring as a process tracing methodology in decision making research. *Journal of Neuroscience, Psychology, and Economics*, *4*(2), 125–146. https://doi.org/10.1037/a0020692

Glöckner, A., & Betsch, T. (2008a). Modeling option and strategy choices with connectionist networks: Towards an integrative model of automatic and deliberate decision making. *Judgment and Decision Making*, *3*(3), 215–228.

Glöckner, A., & Betsch, T. (2008b). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(5), 1055–1075. https://doi.org/10.1037/0278-7393.34.5.1055

Glöckner, A., & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologica*, *139*(3), 532–542. https://doi.org/10.1016/j.actpsy.2012.01.009

Glöckner, A., Betsch, T., & Schindler, N. (2010). Coherence shifts in probabilistic inference tasks. *Journal of Behavioral Decision Making*, *23*(5), 439–462. https://doi.org/10.1002/bdm.668

Glöckner, A., & Herbold, A.-K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making*, *24*(1), 71–98. https://doi.org/10.1002/bdm.684

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666. https://doi.org/10.1016/j.cognition.2014.08.017

Gluth, S., Kern, N., Kortmann, M., & Vitali, C. L. (2020). Value-based attention but not divisive normalization influence decisions with multiple alternatives. *Nature human behaviour*, *4*(6), 634–645. https://doi.org/10.1038/s41562-020-0822-0

Hausmann, D., & Läge, D. (2008). Sequential evidence accumulation in decision making: The individual desired level of confidence can explain the extent of information acquisition. *Judgment and Decision Making*, *3*(3), 229–243.

Holyoak, K. J., & Simon, D. (1999). Bidirectional reasoning in decision making by constraint satisfaction. *Journal of Experimental Psychology: General*, *128*(1), 3–31. https://doi.org/10.1037/0096-3445.128.1.3

Ibraheem, N. A., Hasan, M. M., Khan, R. Z., & Mishra, P. K. (2012). Understanding color models: A review. *ARPN Journal of Science and Technology*, *2*(3), 265–275.

Jekel, M., Glöckner, A., & Bröder, A. (2018). A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect. *Psychological Review*, *125*(5), 744–768. https://doi.org/10.1037/rev0000107

Jekel, M., Glöckner, A., Fiedler, S., & Bröder, A. (2012). The rationality of different kinds of intuitive decision processes. *Synthese*, *189*(S1), 147–160. https://doi.org/10.1007/s11229-012-0126-7

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krajbich, I., Lu, D., Camerer, C., & Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00193

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences*, *108*(33), 13852–13857. https://doi.org/10.1073/pnas.1101328108

Krajbich, I., & Smith, S. M. (2015). Modeling eye movements and response times in consumer choice. *Journal of Agricultural & Food Industrial Organization*, *13*(1), 55–72. https://doi.org/10.1515/jafio-2015-0016

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review*, *11*(2), 343–352. https://doi.org/10.3758/BF03196581

Lohse, G. L. (1997). Consumer eye movement patterns on yellow pages advertising. *Journal of Advertising*, *26*(1), 61–73. https://doi.org/10.1080/00913367.1997.10673518

Marewski, J. N. (2010). On the theoretical precision and strategy selection problem of a single-strategy approach: A comment on Glöckner, Betsch, and Schindler (2010). *Journal of Behavioral Decision Making*, *23*(5), 463–467. https://doi.org/10.1002/bdm.680

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). Opensesame: An open-source, graphical experiment builder for the social sciences. *Behavior research methods*, *44*(2), 314–324. https://doi.org/10.3758/s13428-011-0168-7

Meißner, M., & Decker, R. (2010). Eye-tracking information processing in choice-based conjoint analysis. *International Journal of Market Research*, *52*(5), 593–612. https://doi.org/10.2501/S147078531020151X

Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, *22*(1), 67–74. https://doi.org/10.1016/j.jcps.2011.10.002

Orquin, J. L., Bagger, M. P., & Loose, S. M. (2013). Learning affects top down and bottom up modulation of eye movements in decision making. *Judgment and Decision Making*, *8*(6), 700–716.

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*(1), 190–206. https://doi.org/10.1016/j.actpsy.2013.06.003

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. https://doi.org/10.1037/0278-7393.14.3.534

Read, S. J., Vanman, E. J., & Miller, L. C. (1997). Connectionism, parallel constraint satisfaction processes, and gestalt principles: (Re)introducing cognitive dynamics to social psychology. *Personality and Social Psychology Review*, *1*(1), 26–53. https://doi.org/10.1207/s15327957pspr0101_3

Reisen, N., Hoffrage, U., & Mast, F. W. (2008). Identifying decision strategies in a consumer choice situation. *Judgment and Decision Making*, *3*(8), 641–658.

Reutskaja, E., Nagel, R., Camerer, C. F., & Rangel, A. (2011). Search dynamics in consumer choice under time pressure: An eye-tracking study. *American Economic Review*, *101*(2), 900–926. https://doi.org/10.1257/aer.101.2.900

Scharf, S. E., Jekel, M., & Glöckner, A. (2021). *Testing an extension of the iCodes model to account for situation, person, and task specific variation in the atraction search effect* (Manuscript submitted for publication).

Scharf, S. E., Wiegelmann, M., & Bröder, A. (2019). Information search in everyday decisions: The generalizability of the attraction search effect. *Judgment & Decision Making*, *14*(4), 488–512.

Sepulveda, P., Usher, M., Davies, N., Benson, A., Ortoleva, P., & Martino, B. D. (2020). Visual attention modulates the integration of goal-relevant evidence and not value. *bioRxiv*, 2020.04.14.031971. https://doi.org/10.1101/2020.04.14.031971

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, *6*(12), 1317–1322. https://doi.org/10.1038/nn1150

Smith, S. M., & Krajbich, I. (2019). Gaze amplifies value in decision making. *Psychological Science*, *30*(1), 116–128. https://doi.org/10.1177/0956797618810521

Söllner, A., Bröder, A., Glöckner, A., & Betsch, T. (2014). Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm. *Acta Psychologica*, *146*, 84–96. https://doi.org/10.1016/j.actpsy.2013.12.007

Tavares, G., Perona, P., & Rangel, A. (2017). The attentional drift diffusion model of simple perceptual decision-making. *Frontiers in Neuroscience*, *11*. https://doi.org/10.3389/fnins.2017.00468

Thagard, P., & Millgram, E. (1997). Inference to the best plan: A coherence theory of decision. In A. Ram & Leake (Eds.), *Goal-driven learning*. MIT Press.

Thagard, P. (2000). *Coherence in thought and action*. MIT Press.

Theeuwes, J. (2010). Top–down and bottom–up control of visual selection. *Acta Psychologica*, *135*(2), 77–99. https://doi.org/10.1016/j.actpsy.2010.02.006

Thomas, A. W., Molter, F., Krajbich, I., Heekeren, H. R., & Mohr, P. N. C. (2019). Gaze bias differences capture individual choice behaviour. *Nature Human Behaviour*, *3*(6), 625–635. https://doi.org/10.1038/s41562-019-0584-8

Table 1

Cue-value patterns, adapted from Bröder et al. (2021), that were used in Experiment 1.

	Pattern 1		Pattern 2		Pattern 3		Pattern 4	
	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
Cue 1	?	?	+	−	+	+	−	−
Cue 2	+	+	−	−	?	?	+	−
Cue 3	−	−	+	+	+	−	?	?
Cue 4	+	−	?	?	−	−	+	+

	Pattern 5		Pattern 6		Pattern 7		Pattern 8	
	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
Cue 1	+	−	+	−	?	?	−	+
Cue 2	−	+	?	?	+	−	+	−
Cue 3	?	?	+	+	−	+	+	−
Cue 4	+	−	−	+	+	+	?	?

Note. + represented positive cue values, − negative cue values, ? represented concealed cue values, that were revealed in the decision phase of the experiment.

Table 2

Cue-value patterns that were used in Experiment 2.

	Pattern 1				Pattern 2			
	Version a		Version b		Version a		Version b	
	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
Cue 1	+	−	−	+	+	−	−	+
Cue 2	+	−	−	+	+	+	+	+
Cue 3	−	+	−	+	−	+	−	+
Cue 4	+	−	+	−	+	−	+	−

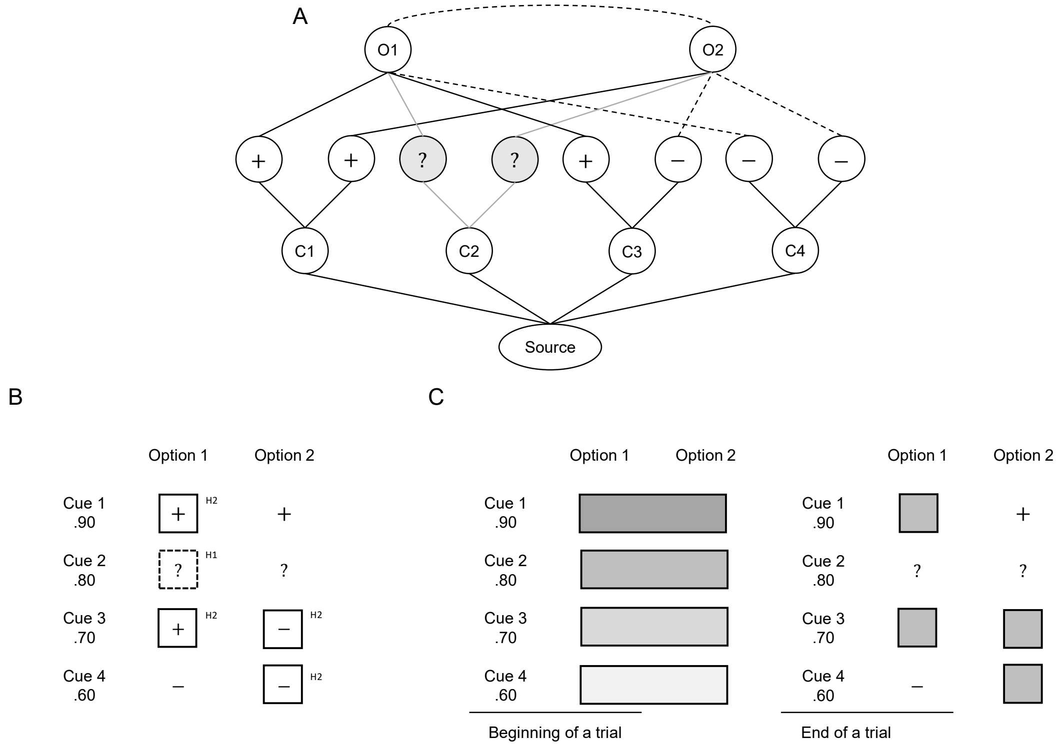
	Pattern 3				Pattern 4			
	Version a		Version b		Version a		Version b	
	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
Cue 1	−	−	−	−	−	+	−	+
Cue 2	+	−	−	+	+	−	+	−
Cue 3	−	+	−	+	+	−	−	+
Cue 4	+	−	+	−	+	−	−	+

	Pattern 5				Pattern 6			
	Version a		Version b		Version a		Version b	
	Option A	Option B	Option A	Option B	Option A	Option B	Option A	Option B
Cue 1	−	+	−	+	−	+	−	+
Cue 2	+	−	+	−	+	−	+	−
Cue 3	+	−	−	+	−	−	−	−
Cue 4	+	+	+	+	+	−	−	+

Note. + = positive information, i.e. the recommendation to buy this stock; − = negative information, i.e. the recommendation to not buy this stock; two cue values were always reversed between Versions a and b and two cue values were kept constant (grey background): for Patterns 1 - 3 Cue 3 and 4 were constant, whereas for Patterns 4 - 6 Cue 1 and 2 were constant.

Figure 1.

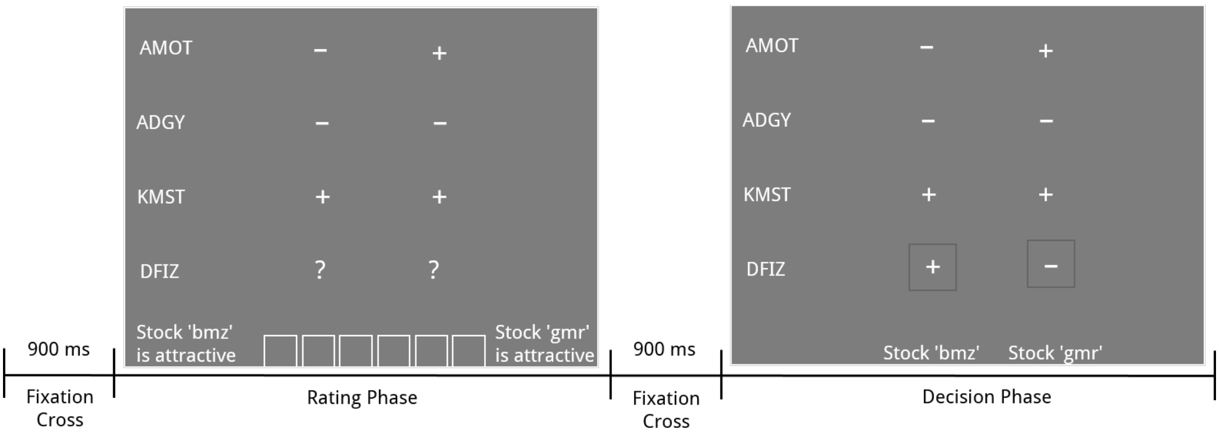
iCodes network and visualization of H1 - H3



Note. A: Black lines represent bidirectional links, grey lines unidirectional links. Continuous lines represent excitatory links, dashed lines inhibitory links. Nodes C1, C2, C3, C4 represent Cue 1, 2, 3, and 4, nodes O1 and O2 Option 1 and Option 2 from the task depicted in B and C. B: Visualization of H1 and H2. H1 (attraction attention effect) predicts that once the concealed information (indicated by "?") is opened, the cue value of Cue 2 for Option 1 (i.e., surrounded by a dashed frame) should be fixated first. H2 (coherence attention effect) predicts that the cue values in the continuous frame should be fixated with a higher probability as they are coherent with the more attractive option Option 1. C: Visualization of H3. H3 (late coherence effect) predicts that in the beginning of the trial (left side) fixations on the cues should be proportional to their respective validities, i.e. more valid cues should be fixated more often than less valid cues (represented by the color gradient from darker to lighter grey). Towards the end of a trial, coherent information (cue values in the light grey frames) should be fixated more often than incoherent cue values while the validity influence on fixation behavior should decrease.

Figure 2.

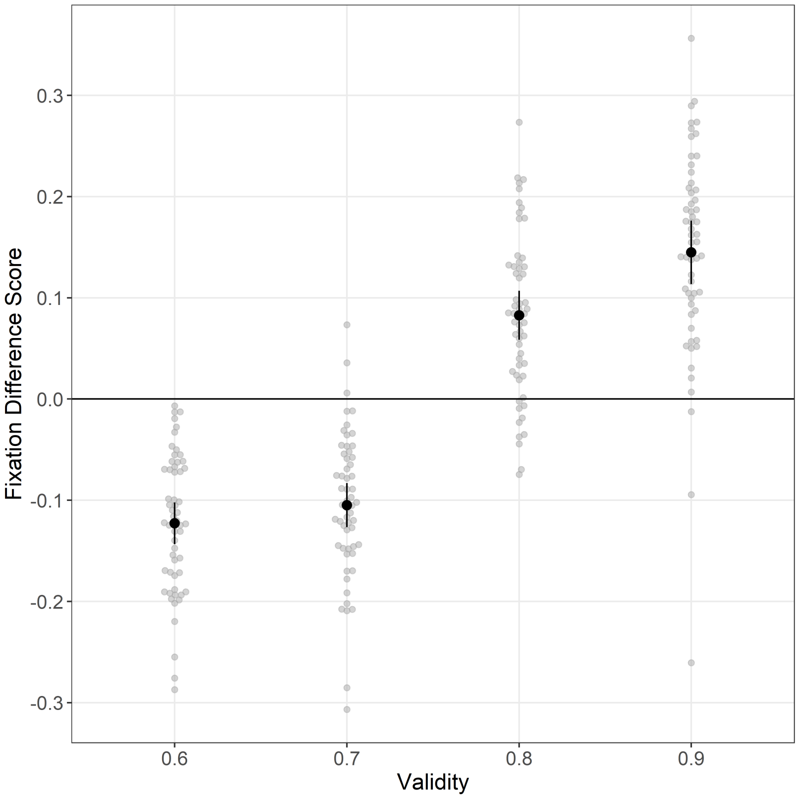
Procedure and reproduced screen displays used in Experiment 1



Note. After the presentation of a fixation cross, participants rated option attractiveness in a self-paced manner. Once they gave their rating, another fixation cross was presented, and participants subsequently made their decision between the options. Participants could respond via the keyboard. Original text was in German. The font size in this display was increased compared to the original for better legibility. Illustration inspired by Fiedler and Glöckner (2012).

Figure 3.

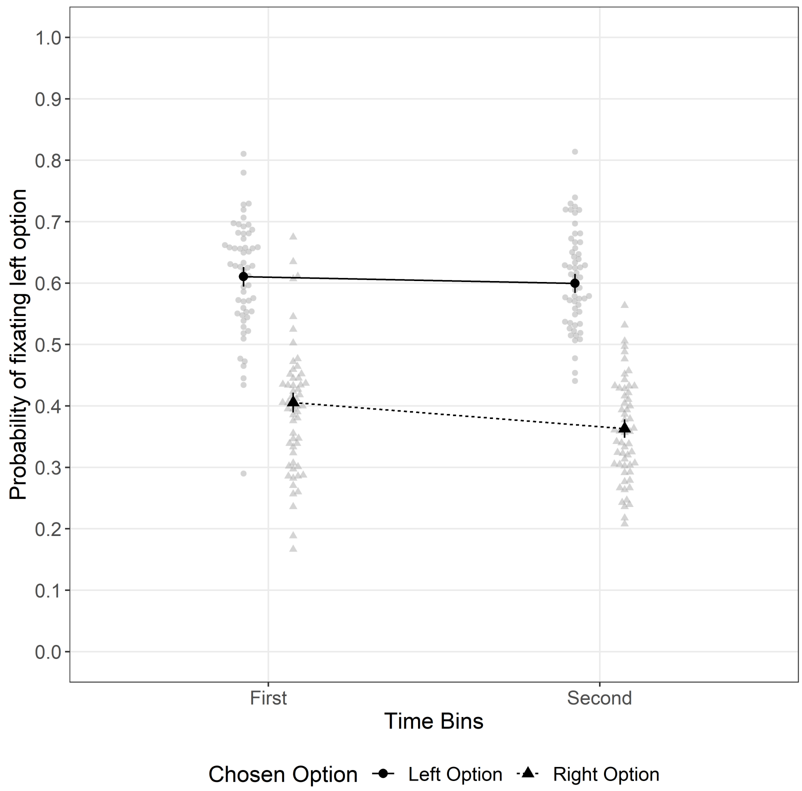
Individual and mean fixation difference scores in Experiment 1



Note. The fixation difference score (FDS) is the difference of the relative fixation frequencies per cue between the first and the second half of a trial. A positive FDS indicates that a cue was fixated more often in the first than in the second half of a trial while a negative FDS indicates the reversed pattern. In the figure, black dots represent mean scores, grey dots individual scores. Error bars represent the within-subjects standard errors.

Figure 4.

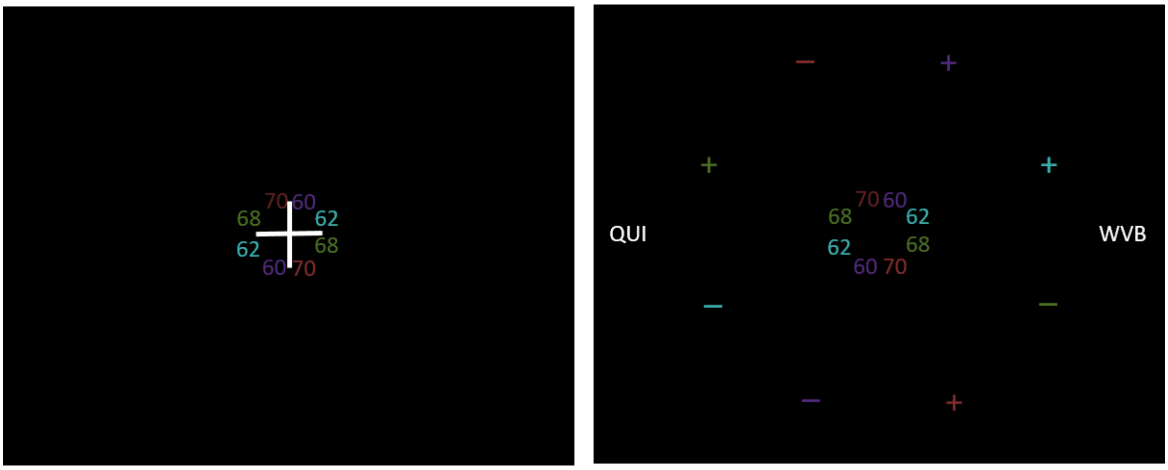
Mean probability of fixating the left option as a function of time in trial and the subsequently chosen option in Experiment 1



Note. Black dots represent the mean fixation probability, grey dots individual fixation probabilities. Error bars represent the model-based standard errors.

Figure 5.

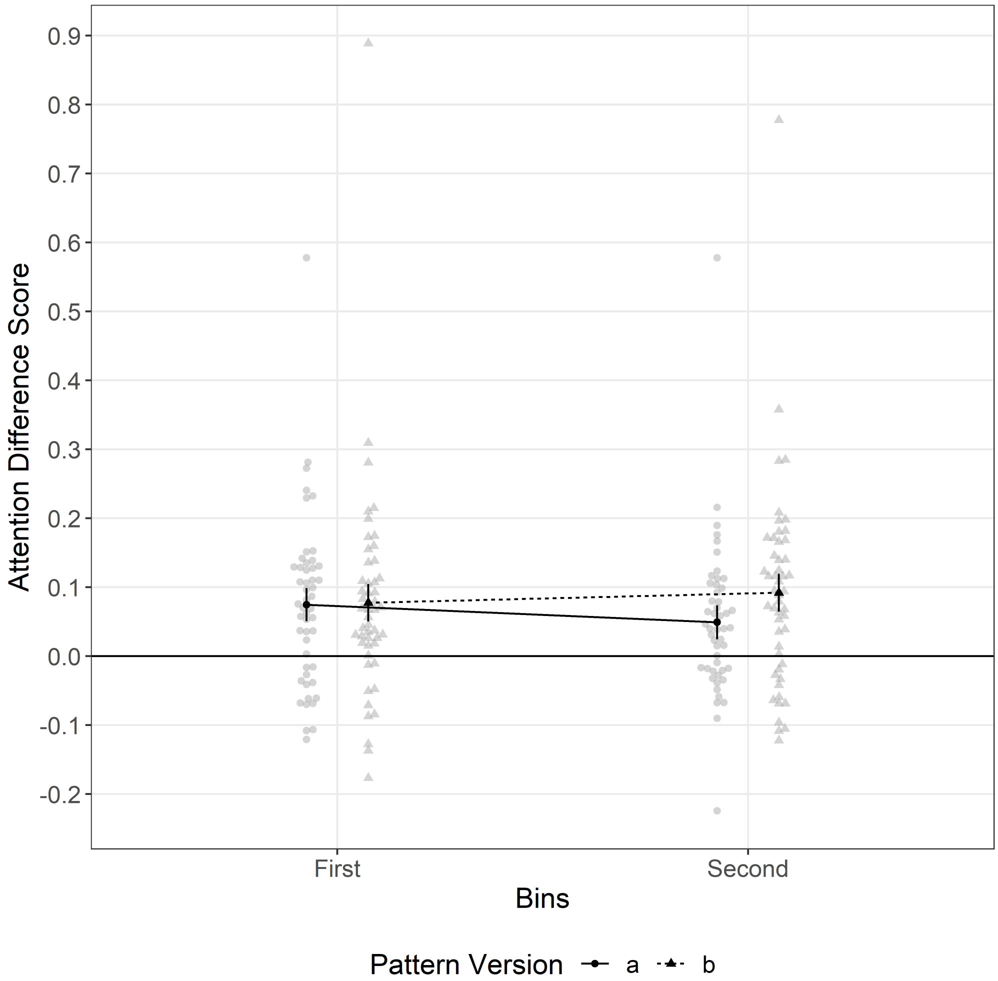
Reproduced screen display of Experiment 1



Note. Fixation cross with validity primer on the left, decision phase on the right. Font size is increased for better legibility.

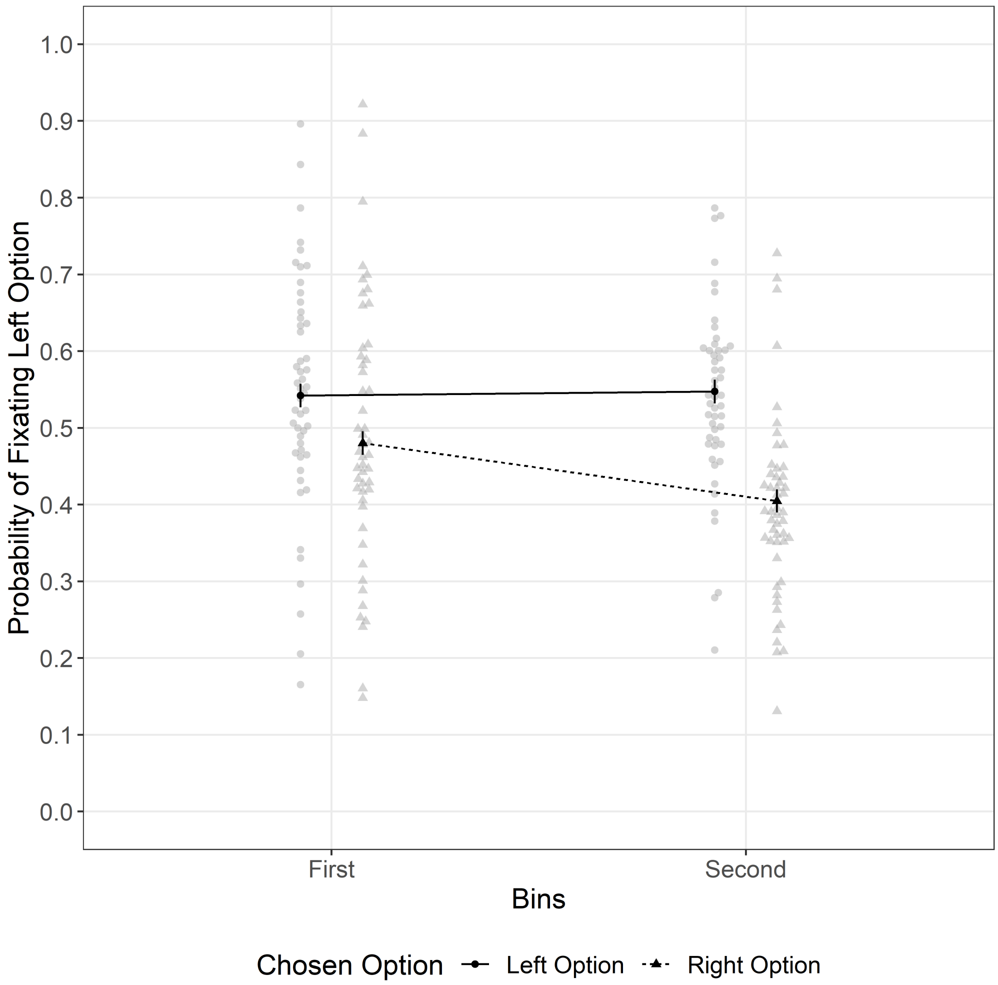
Figure 6.

Individual and mean attention difference scores in Experiment 2



Note. The attention difference score (ADS) is the difference of the relative fixation frequencies of the constant cues. A positive ADS in Version a indicates that the incoherent, constant cue was fixated more often, while a positive ADS in Version b indicates that the coherent, constant cue was fixated more. In the figure, black dots represent mean scores, grey dots individual scores. Error bars represent the within-subjects standard errors.

Figure 7. Mean probability of fixating the left option as a function of time in trial and the subsequently chosen option in Experiment 2



Note. Black dots represent the mean fixation probability, grey dots individual fixation probabilities. Error bars represent the model-based standard errors.

Supplemental Materials

Coherence influences on attention allocation and visual information search in decisions with open information displays

Sophie E. Scharf, Arndt Bröder
University of Mannheim

Marc Jekel, Andreas Glöckner
University of Cologne

Supplemental Materials

Coherence influences on attention allocation and visual information search in decisions with open information displays

Deviations from pre-data reports

The experiments of this article were pre-registered with pre-data report on OSF: https://osf.io/j7v9a/ (Experiment 1), https://osf.io/ykjqr/ (Experiment 2). In these pre-data reports, we reported the hypotheses, sample size rationales, experimental designs, and planned analyses. In the following, we detail in which aspects the article deviates from the pre-data reports and why.

In the pre-data report for the first experiment, there was a mistake in the cue-pattern table: the options were switched in Pattern 1, 6, and 8, such that in these patterns Option B was attractive. The mistake was corrected in the article. In the pre-data report for the second experiment, we did not specify the hypothesis of the gaze cascade effect, as the goal of this experiment was to focus more on the predictions that are specific to iCodes. For consistency reasons, we also tested and reported the gaze cascade effect for Experiment 2 in the current article.

For both experiments, there were deviations from the pre-registered analyses. For instance, we planned to conduct mixed Poisson regressions with the number of fixations per AOI as dependent variable for exploratory analyses for the coherence attention effect (Experiment 1 and 2) and the analysis of the decrease of the validity influence over the course of a trial (Experiment 1). Similarily, to assess the late coherence effect over all cues, we planned to analyze the relative number of fixations per AOI as dependent variable. However, we realized that there was a dependency between the number of fixations per AOI and, thus, that both types of regression models were not appropriate for this way of analyzing AOI-level data. As the design of the experiments and the analyses of gaze data in general were already relatively complex, we opted to refrain from alternative ways of modelling this type of data (such as seemingly unrelated regressions, Srivastava & Dwivedi, 1979; or Markov chain modelling, Button et al., 2011) and put the focus on the simpler aggregate analyses. Alternative linear mixed models that also incorporated the validity and valence of cue values as predictors can be found in the uploaded analyses on OSF.

We also preregistered mixed models for the analyses regarding the late coherence effect in both experiments that we did not report in the main text of the article. For the hypothesized increase of the coherence influence within a trial in Experiment 1, we decided again to report simpler aggregate analyses, as these analyses, in our opinion increased the comprehensibility and their results corresponded to the pre-registered mixed model. This analysis as well as the analysis of the validity of cue values as additional predictor can be found in the uploaded analyses script. Due to the same goal of increased comprehensibility, we decided to only report the preregistered ANOVA for the late coherence effect in Experiment 2: the alternative mixed models did not show the same pattern of results [1] as the preregistered ANOVA. To keep the result section of the article as simple as possible as well as to stay conservative when reporting results, we decided to report only the pre-registered ANOVA.

For the analyses of the late coherence and the gaze cascade effect in Experiment 1, we planned to split the time in each trial into ten equal bins and to bin fixations accordingly. As the average number of fixations per trial was 9.40 in the rating phase and 6.57 in the decision phase of the experiment, we decided against using ten time bins. We opted to report the analyses for two time bins, as this streamlined the results with the analyses of Experiment 2 and in our view increased the clarity of the results. The reported results did not change substantially when binning fixations into four or ten time bins. The same was true for the analyses of the late coherence and gaze cascade effect in Experiment 2.

[1] The mixed model did not show the main effect of pattern version, but did show a small, albeit significant interaction effect of pattern version and time bins. The mixed model based on all cue values on the other hand showed a strong interaction effect as well as a main effect of coherence, yet confounded validity and coherence in its analysis.

Supplemental Analyses

Interaction of gaze cascade effect with coherence

As stated in the article, iCodes predicts that the strength of the gaze cascade effect is moderated by the number of coherent cue values on the subsequently chosen option, such that that the gaze cascade effect should be more pronounced the more coherent information describes the chosen option. As we did not control or manipulate the number of coherent cues per option, we analyzed this prediction exploratorily.

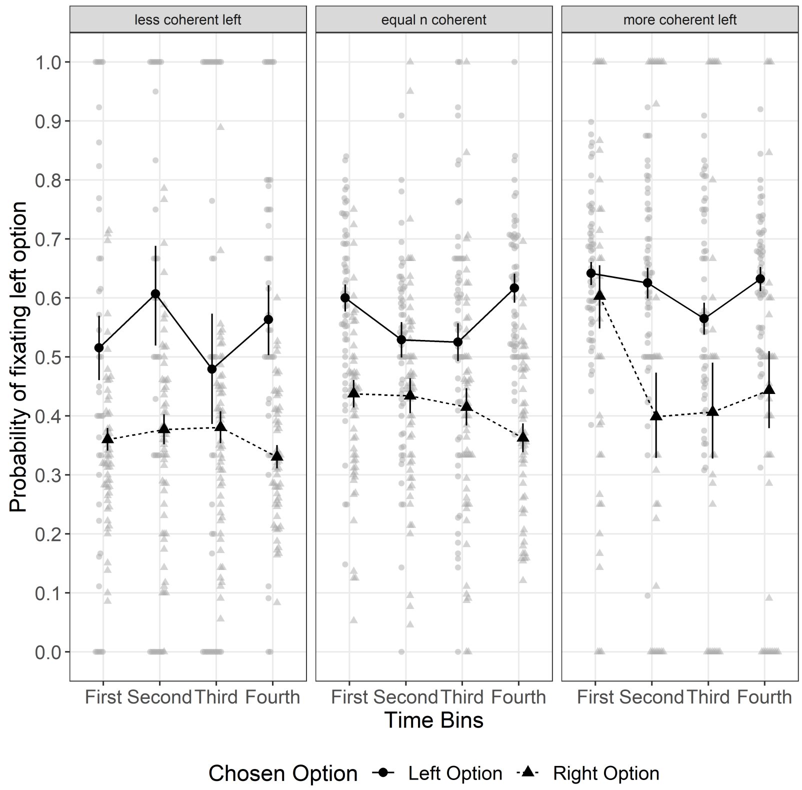
We ran mixed Logistic regressions with whether the left option was fixated (=1) or not (=0) as dependent variable. As predictors we added whether the left option was subsequently chosen (yes = +1, no = −1, effect-coded) and whether there were more, equal, or less coherent cue values on the left option (effect-coded, equal number of cue values as reference group). Further, we added time bins as predictor to the model (first = +1 vs. second = −1 half of the trial). Just as in the original gaze cascade effect model, we also added the z-standardized trial number as predictor and random intercepts for participants. If the amount of coherence on an option moderates the gaze cascade effect, we would expect a significant three-way interaction of the time bins, the chosen option and the amount of coherent information.

In Experiment 1, there were no significant three-way interactions of the relative amount of coherent cues on the left option, the subsequently chosen option, and the time bins. To exploratorily investigate whether the type of bins changes the result, we also ran the same mixed model with four time bins instead of two (Helmert-coded, with the first bin as reference category). This analysis showed three-way interactions, that is that whether there was more coherent information on the left option change the probability of fixating any information on the left option between the first and second time bin, $OR = 1.13$, $z = 3.23$, $p = .001$ (for a visualization of the results, see Figure 1). There was no three-way interaction when binning fixations into ten bins.

In Experiment 2, the number of coherent cue values per option differed for each pattern, such that the predictor of the number of coherent cue values on the left option had only two levels (more coherent cue values left = +1, less coherent cue values left =

Figure 1

Mean probability of fixating the left option as a function of time in trial, the subsequently chosen option, and the amount of coherent information on the left option in Experiment 1



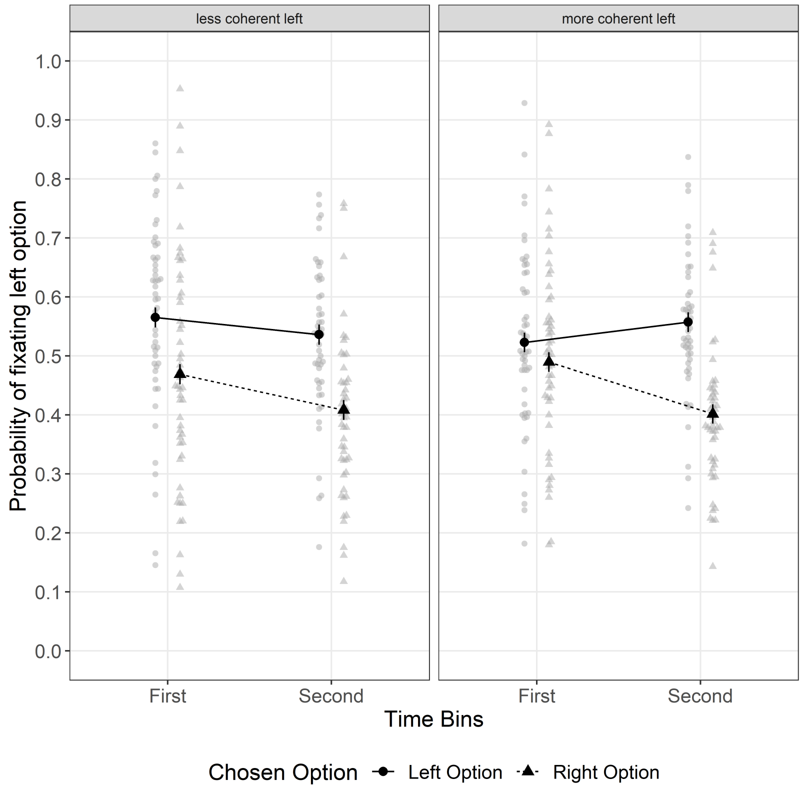
Note. Black dots represent the mean fixation probability, grey dots individual fixation probabilities. Error bars represent the model-based standard errors.

−1, effect-coded). The results of the mixed Logistic regression in Experiment 2 indicated that the predicted three-way interaction of time bins, the subsequently chosen option, and whether there was more coherent information on the left option, was significant, $OR = 0.96$, $z = -6.41$, $p < .001$. The interaction pattern was further in the predicted direction, such that the increase in fixating the subsequently chosen option was more pronounced when there was more coherent information on the chosen option (for a visualization see Figure 1).

Taken together, there was some evidence in our experiments that the amount of coherent information moderated the strength of the gaze cascade effect, as predicted by iCodes. Yet, as the pattern of results was not consistent between Experiment 1 and 2

Figure 2

Mean probability of fixating the left option as a function of time in trial, the subsequently chosen option, and the amount of coherent information on the left option in Experiment 2



Note. Black dots represent the mean fixation probability, grey dots individual fixation probabilities. Error bars represent the model-based standard errors.

and we did not manipulate the amount of coherent information on the more attractive option in both experiments, no definite conclusions can be drawn from these results. Further, more detailed investigations of this prediction of iCodes are warranted.

Correlation of cue-value activations with fixation frequencies

The main assumption behind iCodes's predictions of attention allocation is that the distribution of cue-value node activations can be translated to the distributions of fixations on the cue values. Thus, the activation levels at the cue-value nodes should correlate with the relative frequency of fixations on the cue values. To test this prediction in a first step, we simulated the cue-value node activation for each cue-value pattern with iCodes based on fixed parameters (P = 1.9, cf. Glöckner et al., 2014). We, then, aggregated the mean fixation frequencies per cue-value for each cue-value pattern. We would expect a positive correlation between the aggregated fixation frequencies and cue-value node activations.

In Experiment 1, cue-value node activations and fixation frequencies were positively correlated, $r = .485$, $t(62) = 4.37$, $p < .001$. Cue-value node activations and fixation frequencies were also positively correlated in Experiment 2, $r = .445$, $t(94) = 4.81$, $p < .001$.

Taken together, these results show that, even without fitting individual parameters, cue-value node activations were linked to fixation frequencies. However, it is unclear how much of this correlation can be attributed to validity differences of cue values and the extent to which option attractiveness plays a role in this correlation. Although these results were only preliminary, they highlight the importance of further investigating quantitative model predictions of iCodes. A fruitful avenue for future research could be to create cue-value patterns with distinct activation patterns based on simulations of iCodes and test, whether fixation patterns match these activation patterns.

References

Button, C., Dicks, M., Haines, R., Barker, R., & Davids, K. (2011). Statistical modelling of gaze behaviour as categorical time series: What you should watch to save soccer penalties. *Cognitive Processing*, *12*(3), 235–244.

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666. https://doi.org/10.1016/j.cognition.2014.08.017

Srivastava, V. K., & Dwivedi, T. D. (1979). Estimation of seemingly unrelated regression equations: A brief survey. *Journal of Econometrics*, *10*(1), 15–32.

This dissertation was supported by the *Graduate School of Economic and Social Sciences* (GESS) at the University of Mannheim.

Cover image designed by starline/Freepik.